Parental Investments and Socio-Economic Gradients in Learning across European Countries*

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February 12, 2025

Abstract

There is a widespread belief that strong public investments in children contribute to promote social mobility. Generous maternity leave, affordable daycare, and high-quality public schools, are notable features of Nordic countries. In spite of this, we document that gaps in learning between children of rich and poor parents are as large in Nordic countries as elsewhere in Europe (using data from the PISA and the PIAAC). This is likely the case because parental investments by poor and rich parents are as unequal in Nordic countries as elsewhere in Europe. Through their parental investments, rich parents may be able to undo the equalizing impact of public investments on the learning of their children.

JEL codes: I24, J24, J62, D63

Keywords: Intergenerational Transmission, Inequality, Education, Human Capital.

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1 Introduction

Across the world, in rich and poor countries, there are large socio-economic status (SES) gradients in learning outcomes, measured by schooling or test scores. These gradients in learning emerge early and persist (Carneiro and Heckman, 2002; Schady et al., 2015), and account for a large fraction of the intergenerational transmission of income (e.g., Bolt et al. (2021)).[1] As expected, SES gradients in test scores vary widely across countries, as documented, for example, from the Program for International Student Assessment (PISA), which collects measures of knowledge of math, reading and science, as well as their SES, for 15-year-old adolescents in multiple countries (e.g., OECD (2018)).

In this paper, we show that, surprisingly, SES gradients in PISA scores are not particularly high or low in countries known for low levels of intra and intergenerational income inequality (in particular, Nordic countries: Denmark, Finland, Iceland, Norway and Sweden). Over the past 20 years, these countries have SES gradients in math, reading and science scores, similar to other countries in Europe (especially in the most recent period). This is surprising since Nordic countries are known for having public services which are especially protective of poor families and children, through generous maternity leave, affordable daycare, extensive social safety nets, excellent universal health care, and high-quality public schools. Such services are thought to contribute to a more level playing field, and foster social mobility.

However, it is plausible that SES gradients in learning are primarily driven by differences in parental investments between poor and rich parents, which may (partly) offset the potential equalizing effects of substantial public investments in Nordic countries. This is reminiscent of the argument made by Landerso and Heckman (2017) and Heckman and Landerso (2022) when comparing Denmark and the United States (US). Similar arguments have also recently been made in the United Kingdom (UK) and elsewhere that strong public schools are not enough to induce a significant change in social mobility because they encourage high-SES parents to invest even more to distinguish their children from their lower-SES peers (see, for example, Goldthorpe (2016), and for an older reference with similar arguments, Coleman and Others (1966)).

In support of this idea, we show that SES gradients in the quality of the home learning environment - henceforth referred to as parental investments and measured by the child's access to adequate study conditions, technology, books and art - are as high in Nordic countries as elsewhere in Europe. Furthermore, in any given year, the cross-country correlation between the SES gradients in learning and the SES gradients in parental investments is between 0.70 and 0.80.

[1] Neal and Johnson (1996) and Carneiro et al. (2005) also document that test scores account for the bulk of racial gaps in earnings, while Cameron and Heckman (2001) show that they can fully explain racial gaps in schooling in the United States.

We realize that this is a statistical association that could be potentially driven by a third factor strongly correlated with both gradients. However, it is remarkable how strong this correlation is. Furthermore, because PISA has been administered every 3 years for more than 20 years, we are able to construct a panel of countries. Using this panel, we see that there is not only a strong cross-sectional correlation between SES gradients in parental investments and SES gradients in learning, but also that (within country) changes in SES gradients in parental investment are strongly related to (within country) changes in SES gradients in learning. Over 50% of the (within country) changes in SES gradients in test scores is explained by (within country) changes in SES gradients in parental investments, suggesting that the cross-sectional correlation is not solely due to time-invariant country effects. None of the other country characteristics we examine is as strong a predictor of SES gradients in learning, either in the cross-sectional or panel analysis.[2]

It is not known to what extent the patterns we document have been in place for decades or whether they are a recent phenomenon. To investigate this question, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC), which measures skills in adulthood (while the PISA measures skills in adolescence). Since the PIAAC surveys adults from all age groups, we are able to look at SES gradients in learning over a much wider array of cohorts, although data are available for a more limited set of countries.

We find that, for recent cohorts from the PIAAC (born in 1987 or later, corresponding to those tested in the PISA), Nordic countries do not exhibit particularly high or low SES gradients in test scores, aligning with our findings from the PISA. In contrast, this pattern does not hold for older cohorts. Among older cohorts (born between 1957 and 1966), the cross-country correlation between SES gradients in adult skills and measures of intergenerational elasticity of earnings (IGE) from Corak (2013) is 0.85, reflecting low IGE and low SES gradients in Nordic countries. However, for younger cohorts (born 1987 or later), this correlation drops to 0.13. We provide suggestive evidence that this pattern emerges because the data used to measure IGE in these countries include mainly older cohorts born in the 1960s. Since those taking the PISA have only recently joined the labor market, it is possible that future measures of the IGE, more relevant to the cohorts of individuals taking the PISA, are more correlated with SES gaps in PISA scores.[3]

Finally, the last wave of PISA is for 2022, and tests adolescents right after a period of serious learning disruption induced by the COVID-19 pandemic. Relative to 2018, SES gradients in test scores are slightly higher in 2022 for several countries, but flat or even declining for many

[2]We consider variables that are plausible predictors of intergenerational transmission and for which we were able to assemble at least a partial panel between 2003 and 2018 (e.g., GDP per capita, returns to schooling, difference between top and bottom rates of income tax, government expenditure in education, and school segregation).

[3]Some evidence is emerging that the IGE is rising in Nordic countries relative to the IGE elsewhere (Brandén et al., 2024; Ahrsjö et al., 2023).

others. More importantly, we do not notice any dramatic shift relative to past trends. Before and after COVID-19, there are large SES gradients in learning, that vary substantially across Europe. These gradients are not related to the IGE or school closures during 2020 (a proxy for public investment during COVID-19), but again show a strong association with SES gradients in parental investments in children.

Our main contribution is to document differences across countries and over time in SES gaps in learning, and more important, their determinants. We are able to relate measures of SES gradients in learning and SES gradients in parental investments, which are comparable across a wide variety of countries and over several years.

We focus on learning outcomes to investigate the intergenerational transmission of inequality, while paying particular attention to measurement and comparability of our estimates across countries and over time. The literature documenting the geography of intergenerational transmission (and its trends) has focused mostly on income or years of schooling, rather than on test scores, as proxies for the economic status of children. For example, Chetty et al. (2014) popularized this analysis by documenting the geography of the intergenerational transmission of income in the United States for the 1980-1982 birth cohort. Hertz et al. (2008) and Narayan et al. (2018) document the intergenerational transmission of years of schooling across countries and over time.[4] We expand the focus from income and years of schooling to learning because the former could conceal a part of the picture, since the transmission of inequality from parents to children starts early in the life cycle with the formation of children's human capital (Carneiro and Heckman, 2003; Cunha and Heckman, 2007). We also consider children's success as multi-dimensional and compute SES gradients in test scores, aspirations and non-cognitive skills (Heckman et al., 2006; Deming, 2023). This relates to a growing interest in documenting intergenerational transmission across multiple dimensions, such as wealth (Charles and Hurst, 2003), health (Halliday et al., 2020), attitudes (Dohmen et al., 2011) and non-cognitive development (Attanasio et al., 2022).

To estimate comparable measures of intergenerational transmission of inequality (in academic knowledge) across countries and over time, we use data from PISA and PIAAC and focus on only European countries, rather than on all countries, in these surveys, to examine countries with a more similar set of institutions. Examining cross-country differences in inequality transmission requires using similar datasets and methodologies across countries. However, typical estimates of intergenerational income transmission rely on different datasets and cohorts (Blanden, 2013; Corak, 2013; Stuhler, 2018), raising concerns about comparability. For example,

[4] Alesina et al. (2021), Neidhofer et al. (2018), Deutscher and Mazumder (2020), Acciari et al. (2022), Bell et al. (2023), Corak (2020), and Card et al. (2022) have documented the geography of intergenerational mobility of income or years of schooling in Africa, Latin America, Australia, Italy, England, Canada and United States. Hanushek et al. (2022) show that the socio-economic gradients in test scores have failed to close in the United States over 50 years using multiple datasets.

Grawe (2006) has shown that 40 percent of the variation in the estimates of intergenerational transmission of income across countries can be attributed to the estimation methodology, life cycle bias and different datasets.

We notice that there are several measures of parental SES that can be used. The most traditional is income, which we cannot use because it is not collected in the PISA survey. The two leading alternatives available to us are mother's education and (percentile ranks of) an index of economic, social and cultural status (ESCS) developed by the PISA survey, and based on questions concerning household demographics (including parental education) and assets. Both have advantages and disadvantages. For example, in a country where the proportion of mothers with a high level of education varies substantially across PISA cohorts, the meaning of what it means to be a high-SES family may also change. The ESCS is less immune to this problem, although it is at least partly affected by it since parental education is one of its components. Furthermore, ESCS gaps in learning may be harder to interpret since ESCS does not have a natural scale.

Given these trade-offs, the measure of SES gradients in learning we propose compares the test scores (math) between 15-year-old students, whose mothers have completed high school or above, with students, whose mothers have not completed high school. Importantly, we show that our main results are robust regardless of which measure of SES we use. In addition, they are not driven by changes in the composition of mothers' education and migrants' population.[5] Notably, we show that the main patterns we observe for the SES gradients in math scores and SES gradients in parental investment are robust to excluding one country at a time, changes in the composition of mothers' education and migrants' population, and using the other measures of the SES gradient in learning.

Finally, our study extends the work of Landerso and Heckman (2017) and Heckman and Landerso (2022) by introducing new cross-country evidence on SES gradients in parental investments. We also uncover a strong panel relationship between changes in SES gradients in parental investment and learning across countries and over time.[6] Relative to the official PISA reports (OECD, 2018), we combine data from all available periods, link the intergenerational transmission of learning to measures of inequality and its potential determinants, and analyze its evolution over time. We further explore the findings of Blanden et al. (2023), who previously reported no evidence of a positive relationship – commonly known as the Gatsby Curve (Corak, 2013) – between SES gradients in PISA scores and income inequality, although they did find such a relationship in years of schooling (see also Doepke and Zilibotti (2017, 2019)).

[5]Results are robust to other measures of SES, such as: using father's education, an indicator for whether mothers completed higher education, an indicator for whether mothers have at least the median education within the country and the rank of the SES index of economic, social and cultural status (ESCS) developed by the PISA survey.

[6]We provide suggestive evidence that social norms toward education can constrain how both poor and rich parents invest in their children, even in the presence of equalizing policies.

Using the PIAAC, we present new evidence that the relationship between SES gradients in test scores and income inequality has shifted over time. We show that younger PIAAC cohorts (those who took the PISA in 2003) exhibit no correlation between SES gradients in test scores and either inequality or the IGE, while older cohorts born in the 1960s show strong correlations with both.[7] We highlight that cohorts studied in PISA are younger than those used to analyze the Great Gatsby Curve in years of schooling. This distinction is important for understanding generational differences in inequality transmission.[8]

Overall, our findings illustrate that the potential for public policy to level up opportunities in childhood may be more limited than widely believed. Especially for recent cohorts, disparities in parental investments in children are associated with large disparities in children's learning, even in countries with widespread availability of generous and high-quality health, education and anti-poverty services. Commenting on the apparent failure of UK education policy to promote social mobility, Goldthorpe (2016) argues that the increased competition for scarce high-end jobs (paired with loss aversion) induced richer families to invest even more in their children, in an effort to prevent them from falling down the social ladder. He argues for a more comprehensive bundle of policies to address social mobility, even suggesting that public education may not be the most adequate tool.

This paper is organized as follows. Section 2 discusses the data and the measures of intergenerational transmission of learning outcomes (i.e., SES gradients in test scores). Section 3 describes the geography and trends in the intergenerational transmission of learning in Europe over the last two decades. In Section 4, we compare the intergenerational transmission of learning and some of its possible determinants, exploring the role of parental investments. In Section 5, we extend the analysis to the 2022-PISA wave after COVID-19 and discuss possible implications for the future. Section 6 concludes.

2 Intergenerational transmission of learning

2.1 PISA data

We use individual-level data from the PISA tests, administered every 3 years from 2000 to 2022 by the Organisation for Economic Co-operation and Development (OECD). These data

[7] Unfortunately, data on SES gradients in parental investments across countries for earlier PIAAC cohorts are unavailable. It is possible that high-SES parents were less protective in the past, when inequality levels were lower across European countries.

[8] Durlauf et al. (2022) review explanations for the Great Gatsby curve, including credit constraints (Becker and Tomes, 1979; Becker, 1991; Solon, 1999), sorting and segregation (Durlauf and Seshadri, 2018), and aspirations (La Ferrara, 2019). Recent critiques, such as Mogstad and Torsvik (2023), argue that the curve is driven by a few outlier countries, while Karlson and Landersø (2021) suggest that intergenerational mobility reflects stages of development. Additionally, DiPrete (2020) notes that discrepancies arise from how inequality and mobility are measured, particularly regarding the role of taxes and transfers.

contain information on 15-year-old students' learning outcomes in reading, mathematics and science. Learning outcomes are measured via tests, meant to determine students' preparation in important courses as well as for their adult life. Our analysis focuses on test scores for 24 European nations that have taken the tests at least six waves in a row. Appendix Table A1 reports the countries in the analysis.

For the PISA test, typically, each country selects between 4,500 and 10,000 students through a two-stage stratified sampling technique. A random sample of at least 150 schools, enrolling 15-year-old students, is drawn first. Then, 35 students within each school are randomly selected to take part in the test. Each student responds to a randomly selected subset of questions from a larger pool.

PISA test scores are explicitly designed to allow comparisons across countries and over time. To make test scores comparable, they are not presented as point estimates, but as "plausible values". These values are computed by drawing random plausible values for each student from a probability distribution of test scores based on the student's answers (OECD, 2011). To ensure comparability, we use plausible values and survey weights throughout the analysis. First, using the plausible values accounts for the latent nature of test scores and produces a more precise representation of the associated uncertainty. Second, the inclusion of survey weights, as provided by PISA, allows for the estimation of population-level parameters, ensuring the representativeness of the findings within the target population. We therefore estimate the regression models iteratively, employing different plausible values for the dependent variable in each iteration and survey weights, to effectively tackle the intricate nature of the PISA data (see, for example, Jerrim et al. (2017)).

Every wave of the PISA data also includes a student, parent and school questionnaire. These questionnaires provide a wide range of information on students' and parents' characteristics, such as parents' education, educational investment in their children, and home resources. We use this information to measure parents' socio-economic status, which we discuss in detail in Section 2.2.

We finally check to what extent the data on parental SES in the PISA conforms with data available from other sources. Appendix Figure A1 presents a validation of the measures collected in the PISA dataset against external data sources from the World Bank Database. Panel A of Appendix Figure A1 demonstrates a strong and close to 0.90 correlation between the proportion of mothers with at least upper secondary education (average over 7 PISA waves) and the proportion of females (aged 25+) with at least upper secondary education (World Bank database). Similarly, Panel B of Appendix Figure A1 presents the correlation between the standard deviation of the PISA index of economic, social and cultural status (ESCS) and the Gini coefficient from the World Bank, which is also reasonably high, reaching almost 0.60.[9]

[9]The Educational, Social, and Cultural Status (ESCS) index in PISA is a composite measure that captures

2.2 Measuring intergenerational transmission of learning

In this section, we discuss the measures of intergenerational transmission of learning (i.e., SES gradients in test scores/intergenerational mobility in learning) that we use throughout the paper. Each measure has its own advantages and disadvantages. To aid in interpretation, we begin with the association between the child's test score and the mother's education, using an indicator for whether the mother has completed at least upper secondary schooling (Appendix Table A2 describes the ISCED levels).

For each student i in country c, cohort t and subject k, we estimate:

$$R(Y_{itc}^k) = \alpha_{tc}^k + \beta_{tc}^k HS_{itc}^P + \epsilon_{itc}^k \quad (1)$$

where $R(Y_{itc}^k)$ is the test score percentile rank, computed at European level, for subject k, for student i, at time t, living in country c. HS_{itc}^p is an indicator variable taking value 1 if student i's mother has completed at least upper secondary education, and 0 otherwise. Throughout the analysis, we use the survey weights and plausible values provided by the OECD to account for the complexities of the PISA test and assure comparability of test scores over time and across countries (see Section 2.1).

β_{tc}^k measures the association between the mother's education (at least upper secondary education) and her child's rank in the distribution of math scores, for cohort t in country c. This represents a measure of the *SES gradient in learning*, which captures the difference in learning ranks between children whose mothers have different levels of schooling. Therefore, higher values of this parameter correspond to lower mobility (more persistence in the transmission of learning outcomes).

α_{tc}^k is the average learning rank for students whose mothers do not have a high school degree for cohort t in country c. This is a measure of *upward mobility* (higher values correspond to more mobility).

Both are important measures of intergenerational transmission of learning (SES gradients in learning): the former is a measure of relative inequality between children of more and less advantaged families, while the latter is a measure of how well children of disadvantaged families perform.

In the paper, we present estimates for the math percentile rank, computed at the European level, and mother's education as we consider it easier to interpret and more comparable from a policy perspective. This also brings attention to a form of inequality transmission related to escaping the lower ranks of the education distribution, an issue we may be particularly concerned about. But more importantly, we show that the estimates are robust to: alternate measures of

the socio-economic background of students participating in the assessment. It combines information on various indicators, such as parental education, occupation, and possessions (like owning a car, among other variables), to provide a summary measure of a student's social and cultural capital.

rank (European vs. country rank), definitions of parental socio-economic background, changes in composition and other measures of children's success. In Sections 3 and 4.3, we show that results are consistent across alternative SES measures, including father's education, an indicator for whether mothers completed higher education, an indicator for whether mothers have at least the median education within the country, and the rank of the SES index of economic, social, and cultural status (ESCS) developed by the PISA team. We also show that the relationship between SES gradients in learning and SES gradients in parental investment is robust to excluding one country at a time, changes in composition of mothers' education and migrants' population, and using alternative SES gradient measures detailed in the appendix.

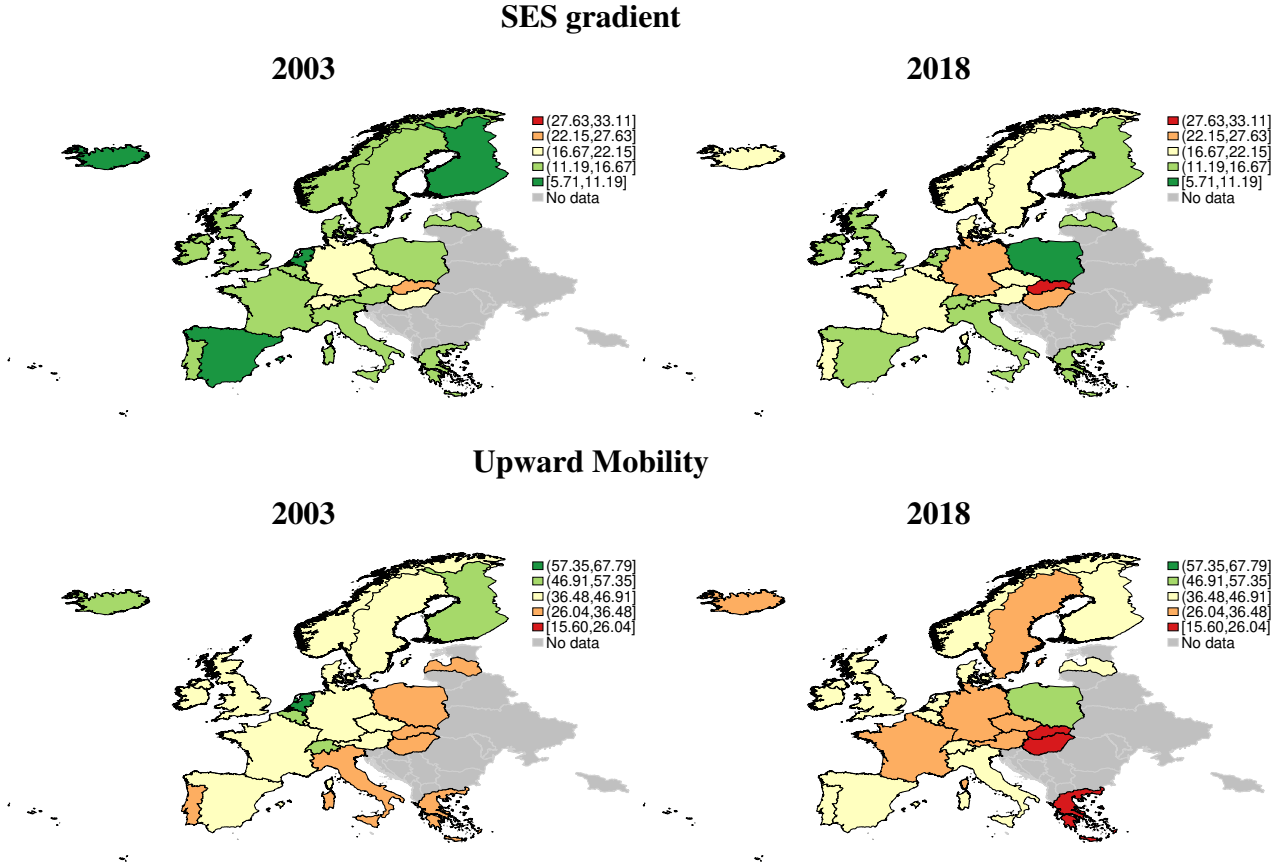
Estimates of intergenerational transmission of learning are presented from 2003 because PISA begins to collect data on parental investment only from 2003 onwards. Measures of intergenerational transmission of learning for 2000 are available in Appendix Table A.2. We finally present estimates for the 2022 wave (after COVID-19) in Section 5.

3 Intergenerational transmission of learning across Europe and over time

As discussed in the Introduction and Section 2, we begin by presenting the estimates for the intergenerational transmission using the student i's math test score (rank), $R(Y_{itc}^{math})$, and start with the estimates of SES gradient (β_{tc}^{math}) and upward mobility (α_{tc}^{math}) for different European countries and different cohorts, based on equation (1). Figure 1 presents a heat map of these measures for 2003 and 2018 PISA waves. Green areas represent countries where inequality is less likely to be transmitted from parents to children (low β_{tc}^{math} in the case of the SES gradient in learning, and high α_{tc}^{math} in the case of upward mobility), whereas red areas indicate countries with greater transmission.

Take for example Germany, which is one of the countries with the highest SES gradients in learning in our sample (even though it is not a country with particularly high or low IGE, as documented in Corak (2013)). In 2003, the SES gradient in learning, β_{tc}^{math}, was equal to 22, while the corresponding value for 2018 was 26. This means that, in Germany in 2003, children whose mothers completed upper secondary education were 22 percentiles above children whose mothers did not complete upper secondary education in the European distribution of PISA scores in math. This difference rose to 26 percentiles in 2018, which means that SES gradients in learning increased in Germany during this period. In 2003, the upward mobility, α_{tc}^{math}, was equal to 39, while the corresponding value for 2018 was 31. On average, children whose mothers did not complete upper secondary education scored in 39^{th} percentile of the PISA distribution in 2003, while in 2018 their performance decreased to the 31^{st} percentile (see Appendix Table A.2).

Figure 1: Heat map of intergenerational transmission of learning (math score)



Note. The heat maps present the estimates of intergenerational transmission of learning for each country and cohort (the estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least upper secondary). The SES gradient in learning measure is β_{tc}^{math} from equation (1). The upward mobility (α_{tc}^{math}) is the average rank of test score of children whose mothers do not have upper secondary. The rank is computed at the European level. Green areas are the most mobile and red areas are the least mobile. The intervals are the same for each year.

Together with Hungary and Slovakia, Germany is one of the three countries with the larger SES gradient in learning in Europe in 2003. Even though low-SES German students perform much worse than their high-SES counterparts, they perform much better than low-SES students in several other countries, such as Hungary, Slovakia, Poland, Italy, Greece, or Portugal. The countries with the lowest SES gradients in learning in 2003 are the Netherlands, Iceland, Spain and Finland. The Netherlands and Finland are also the two countries where students from low-SES backgrounds perform best across Europe.

By 2018, most (but not all) countries have lower levels of intergenerational transmission of learning than in 2003. The countries with the lowest levels of SES gradients in learning are still Germany, Hungary and Slovakia, and as in 2003, students of low-SES status perform much better in Germany than in either Hungary and Slovakia (which, together with Greece, are the countries with the lowest performance of low-SES students in 2018). In this year, Poland is by far the country with the highest levels of intergenerational transmission of learning among those in our sample.

There is however substantial stability between 2003 and 2018 in the relative position of countries in the sample. Appendix Figure A2 shows that the correlation in the estimates of the SES gradient in learning across countries between 2003 and 2018 is 0.7 (it is 0.8 between 2003 and 2009, and 0.93 between 2009 and 2018), while for upward mobility this correlation between 2003 and 2018 is 0.51 (0.65 for 2003 to 2009, and 0.94 for 2009 to 2018).

It is interesting that some of the larger deviations from this stability occur in Nordic countries. Sweden, Finland and Iceland (together with Slovakia and the Netherlands) are among the 5 countries where intergenerational transmission of learning decreased the most between 2003 and 2018 (Appendix Figure A3). In addition, we observe that, across cohorts, SES gradients in test scores in the USA are similar to those in Europe (see Appendix Figure A4 for the estimates of the intergenerational transmission of learning in the United States). Consistent with the arguments in Landerso and Heckman (2017) and Heckman and Landerso (2022), there is little difference between SES gradients in PISA scores between the USA and Denmark.

We finally document that these patterns are robust to: alternate measures of rank, parental socio-economic background, and children's success, as well as changes in composition of migrant population and mother's education.

First, Appendix Table A4 shows that our results are robust to alternate measures of rank.[10] This is because there is a good overlap in the test score distributions across different countries (Appendix Tables A5 and A6). The correlation between the two measures (rank at the European vs rank at the country level) is high - 0.99 for β_{tc}^{k} and 0.67 for α_{tc}^{k}. Results are also robust to using alternate definitions of parental socio-economic background, such as: (i) an indicator for whether the father has completed upper secondary education, (ii) an indicator for whether the mother has higher education, (iii) an indicator for whether the mother has at least the median education within the country and (iv) the rank of the index of economic, social and cultural status (ESCS) constructed by the PISA. Appendix Table A4 shows the correlations among these estimates, which are usually above 0.60. Section 4.5 presents SES gradients in other dimensions of children's success, such as reading, science, educational aspiration, occupational aspiration and being on time to school.

Second, we document that these patterns are robust to considering only the native population (Appendix Figure A5) and notice that the correlation between the main measure and the one computed restricting the sample to the native population is 0.91, statistically significant. In addition, there is no correlation between the proportion of first- and second-generation migrant students in the country and our estimates of intergenerational transmission of learning (Appendix Table A7).

[10]The European rank is constructed by ordering each plausible value of the test scores in ascending order within Europe, using the weights provided by PISA. The advantage of using a European rather than a country-level rank is that the effect of mother's education on test score is more comparable, as we are using the same distribution of test scores.

Third, we notice that the proportion of children, whose mothers have less than upper secondary schooling, varies substantially across countries, and even across time. We document that there is no clear correlation between the proportion of mothers with low levels of education and our estimates of intergenerational transmission of learning (Appendix Table A8). If anything, there is a non-significant correlation which is hard to make sense under the most-standard selection mechanism. As the proportion of disadvantaged children declines, we would expect that the remaining disadvantaged children, if anything, have worse unobservables. After all, these are the ones that stay behind in a society where disadvantage (at least on this measure) is declining. If that is a reasonable hypothesis, the estimated correlation with the proportion of disadvantaged children should go in the opposite directions for the SES gradient in learning and upward mobility.

Ultimately, Section 4 documents that the relationship between SES gradients in learning and SES gradients in parental investment is robust to excluding one country at a time, compositional changes, and other measures of SES gradients in learning described in the appendix.

4 Correlates: intergenerational transmission of learning

What drives differences across countries, and changes over time, in SES gradients in learning? This is an important, but difficult question to answer. Even if we identify important correlates of cross-country variation in SES gradients in learning, it is difficult to establish that they are causal drivers.

It turns out, however, that it is difficult to identify important correlates of SES gradients in learning to start with. Surprisingly, there are not many variables strongly correlated with SES gradients in learning. We explore this for SES gradients in learning in Sections 4.1-4.3 and then turn to upward mobility and SES gradients in other traits in Sections 4.4 and 4.5.

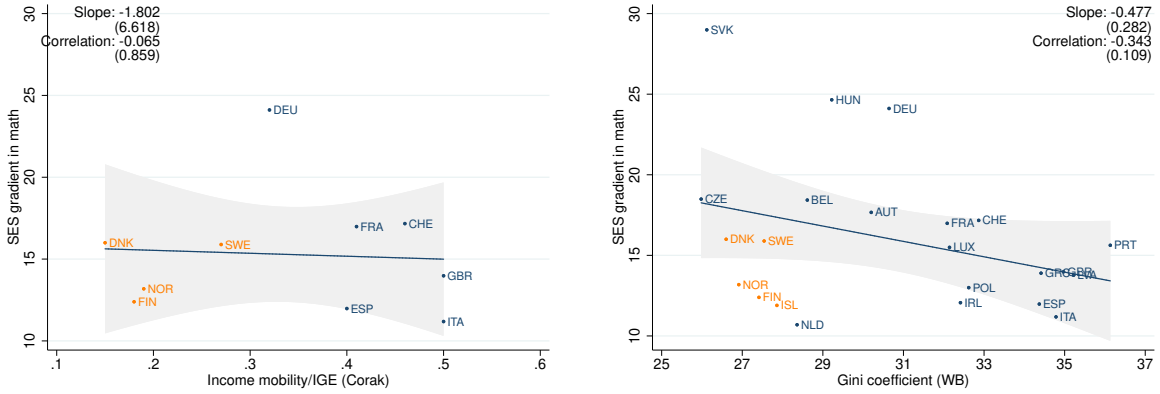
4.1 Intergenerational transmission of learning and inequality

We begin by asking if there is a relationship between SES gradients in learning and inter and intra-generational inequality. There are several reasons why one might observe such relationship. To the extent that human capital is an important determinant of earnings, it is perhaps natural to ask whether there is a relationship relating SES gradients in learning to inequality across countries.

First, we document that surprisingly SES gradients in PISA scores are *not* correlated with estimates of the intergenerational mobility in income across countries (left panel of Figure 2). The estimates of income mobility come from Corak (2013), who compiles a dataset of IGE estimates from published studies, adjusting them for methodological comparability. These es-

timates are for the cohort of children born during the early to mid-1960s, with their adult outcomes measured in the mid to late 1990s (Corak, 2013). As a robustness, we also reproduce the left panel of Figure 2 by using estimates of inequality of opportunity, available for a larger set of countries, and reach a similar conclusion (Appendix Figure B1).

Figure 2: Correlation between SES gradients in math, IGE (Corak, 2013), and Gini



Note. The Left Figure presents the correlation between SES gradients in math (math - averaged over PISA years) and income mobility measure from Corak (2013). Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). The Right Figure present the correlation between the SES gradient inmath and Gini coefficient from the World Bank (averaged over all PISA years). The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Second, we ask if there is a positive cross-country relationship between SES gradients in learning and inequality in the society, known as the Great Gatsby curve (Corak, 2013), which has been widely discussed in the academic and popular press. It is observed not only across countries, but also within (Chetty et al., 2014; Corak, 2020). It has however also been subject of controversy (Mogstad and Torsvik, 2023). We document that SES gradients in PISA scores are, if anything, negatively correlated with income inequality (right panel of Figure 2). As a whole, Nordic countries, which have the lowest income inequality in Europe, do not have smaller SES gradients in PISA scores than countries with high income inequality, such as Great Britain, Poland, Latvia or Portugal.[11]

We show that even when we use other measures of inequality or intergenerational transmission of learning this correlation is often zero, but never positive. We find no evidence for the Great Gatsby curve when we reproduce the right panel of Figure 2 by: (i) linking the SES gradients in learning from each PISA wave to the Gini coefficient (World Bank) (Appendix Figure B2), (ii) using the standard deviation of the ESCS index, built by PISA, to measure inequality in ESCS in any of the PISA cohorts (Appendix Figure B3), (iii) using other definitions of SES gradients to measure intergenerational transmission of learning, such as rank-rank coefficients

[11]Nordic countries (Denmark, Finland, Iceland, Norway, and Sweden) are abbreviated with three-letter codes (DNK, FIN, ISL, NOR, and SWE) in the figures.

from regressing the rank of the test score on the rank of ESCS (Appendix Figure B4 and Appendix Table B1), and (iv) using data from other international assessments, such as the Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) studies, to measure learning (Appendix Figure B5 and Cardim and Carneiro (2021)).[12]

These findings hint towards the emergence of a poverty trap in education. Relative to other countries, rich parents in Nordic countries are not particularly impaired (e.g., by the progressivity of the tax system) when it comes to invest productively in their children. Furthermore, relative to other countries, poor parents in Nordic countries are not especially helped by the strong welfare state when it concerns their children's learning.[13] We turn to this next by first exploring when these patterns have emerged in Section 4.2 and then by exploring other possible correlates of SES gradients in learning in Section 4.3.

4.2 Using PIAAC to study older cohorts

These surprising results lead us to undertake further analysis measuring literacy and numeracy using comparable assessments across countries, but this time in a population of adults: the Programme for the International Assessment of Adult Competencies (PIAAC), also collected by the OECD. There are differences and similarities between the PIAAC and PISA, extensively discussed in many documents (e.g., Gal and Tout (2014)), the most obvious of which is that PISA measures skills in adolescence, and PIAAC measures skills in adulthood.

One important feature of the PIAAC sample (2012) is that its youngest respondents born in 1987 or later belong to the same cohorts that took the PISA test in 2003. In fact, when we compare SES gradients in learning for the same cohorts taking PISA and PIAAC, the correlation between the two measures is about 0.7, statistically significant (Appendix Figure B7).

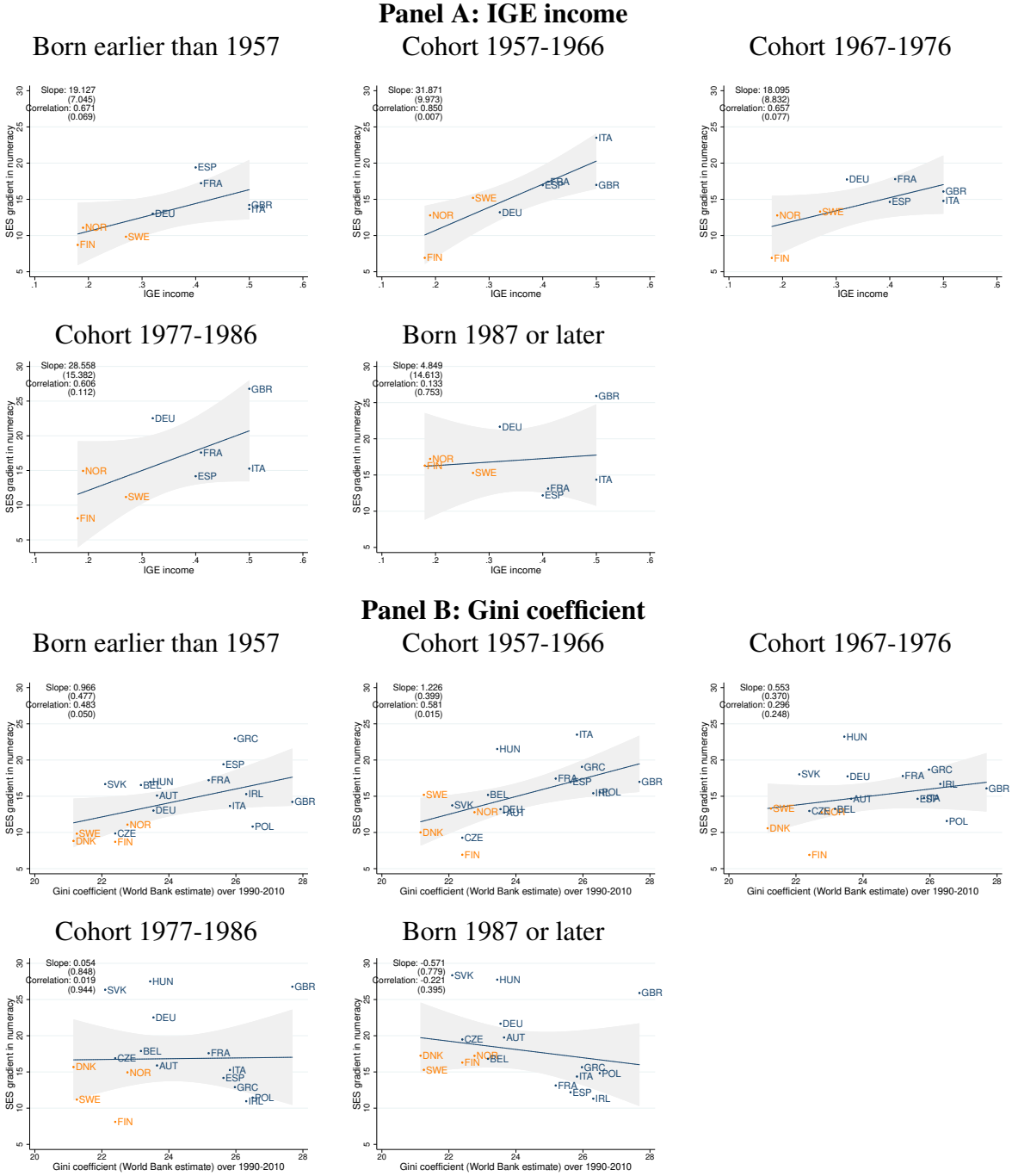
We therefore divide the PIAAC sample into different cohorts (or age groups), and estimate, for each cohort the (cross-country) correlation between SES gradients in test scores and the IGE estimates compiled by Corak (2013) for the cohort born in 1960, and the correlation between SES gradients in test scores and inequality (Gini coefficient from the World Bank, averaged over 1990-2010). The results, reported in Figure 3, are quite striking. They show that, for younger cohorts (the ones also surveyed in the initial waves of the PISA), there is no correlation between SES gradients in test scores and the IGE, or between SES gradients in test scores and inequality.

On the other hand, both these correlations are positive and large for older cohorts. It is

[12] Appendix Figure B6 shows that there is a strong cross-country correlation between SES gradients in learning measured in the TIMSS/PIRLS and PISA.

[13] It is possible that, as argued in Landerso and Heckman (2017) and Heckman and Landerso (2022), higher SES parents in Nordic countries are just much better at accessing all the public benefits offered in their countries, so that the generous provision of these benefits does not equalize SES gradients (what they call the Matthew Principle).

Figure 3: PIAAC - correlation between SES gradients in numeracy, IGE (Corak, 2013), Gini coefficient



Note. The figures present the correlation between SES gradients in numeracy and IGE income (Corak (2013)'s sample) in Panel A and the correlation between SES gradients in numeracy and Gini coefficient (averaged over 1990-2010) in Panel B. Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). The mobility measure is the β_{tc}^{k} from regressing the rank of numeracy skill on a dummy equal to 1 if the mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

possible that this is due to an age effect. Perhaps the age at the time one takes the PIAAC

test really matters for how well one performs on that test. We believe, however, that it is more likely that these differences are due to cohort effects, given the design of the PIAAC test. For these older cohorts (but not for the younger cohorts), SES gradients in learning are the lowest in Nordic countries (as well as the Czech Republic and Poland), which are also the countries with the lowest IGE and lowest levels of inequality.

We do not know what changed, but it is worth noting that the lowest SES gradients in test scores are observed among older cohorts in the Nordic countries in the PIAAC data.It is only in recent cohorts of the PIAAC that the relative position of Nordic countries changes. Furthermore, as discussed above, for several Nordic countries SES gradients in PISA scores appear to increase between 2003 and 2018. The top 5 countries in Europe experiencing the largest increases in these gradients are Sweden, Iceland and Finland, together with the Netherlands and Slovakia.

In sum, some of the Nordic countries appear to be on a trend to higher skill-inequality by family background, making them more similar to other countries in Europe, and this trend seems to have started several cohorts ago (Appendix Figure B8). At this point, we can only speculate about the sources of these changes. We turn to some descriptive results that may help illuminate this issue in Section 4.3.

4.3 Public and private investments in children

In this section, we look at other potential correlates of SES gradients in PISA scores. Since we have constructed a panel database of SES gradients in tests scores across countries, it is possible to examine not only cross-sectional correlations, but also to study whether changes in particular variables are correlated with changes in SES gradients in test scores across different cohorts in each country.

4.3.1 Cross-sectional analysis

Here we start by looking at cross-sectional associations. We consider different sets of variables that can contribute to differences in learning outcomes across SES groups: *socio-economic variables* (returns to secondary school from the OECD, and country GDP per capita from the World Bank database); *institutional variables* (the progressivity of the tax system, proxied by the difference between the top and lowest tax rates on personal income, and spending in public education from the World Bank database) and *education system variables* (age at which academic tracking starts from Eurydice and school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects).

A final variable concerns parental investments in children, in particular, the SES gradients in parental investments. To measure parental investment in children, we estimate a factor model with categorical items using data from the students' questionnaire, which includes information

on home educational resources, such as the child's access to adequate study conditions, technology, books and art. The factor model, described in detail in Appendix B.5.1, allows us to set the scaling assumption to obtain a comparable measure of parental investment across countries and over time.

We therefore measure the socio-economic gradient in parental investment by estimating a specification similar to equation (1), where we regress the rank of parental investment at European level on an indicator variable equal to 1 if the mother has completed at least upper secondary. It is important to highlight that this measure of parental investment mostly captures material investment. We note that material investment has been shown to be important for cognitive outcomes, while time investment is important for non-cognitive outcomes (Attanasio et al., 2020). Additionally, we investigate a plausible concern about whether the SES gradients in parental investment capture the same information as the ESCS index built by PISA, a proxy of family socio-economic background, and notice three things.

First, the ESCS is measured by combining information about parental education, occupation and possessions, such as cars, while parental investment is measured by combining information on home environmental inputs, such as possession of a desk, study space, literature. Second, Appendix Figure B9 shows a lack of correlation between inequality in ESCS and SES gradients in parental investments, hinting that inequality in the ESCS and SES gradients in parental investment are measuring two different factors. Third, PISA also collects some information on parental time investment from Portugal, Italy, Germany, and Belgium in 2012, 2015 and 2018. We notice that, for this subset of countries, SES gradients in parental investment (Appendix B.5.1) and SES gradients in time investment are positively correlated (0.3 for the three waves pooled together, while the correlation for 2018 is 0.7).[14]

We begin by showing the correlation between each of these variables (averaged over all PISA years) and SES gradients in math scores (averaged over all PISA years) in Table 1. The variables most correlated with SES gradients in learning are: the age at which academic tracking starts, school segregation, and the SES gradients in parental investments. If we regress SES gradients in PISA scores on all variables considered in Table 1, the school age tracking and SES gradients in parental investment survive and remain statistically significant (Column (8)).[15]

School tracking age has been documented to be relevant to explain the SES gradient in learning (Pekkarinen et al., 2009; Pekkala Kerr et al., 2013; Ferreira and Gignoux, 2013), a finding we confirm in our study. Systems, where the placement of students into academic tracks

[14] We construct a measure for the SES gradients in time investment by combining information on frequency of the following activities between the parents and the children: parents discuss how well my child is doing at school, parents eat <the main meal> with my child around, parents spend time just talking to my child, parents help child with his/her reading and writing, parents discuss political or social issues with child, parents go to a bookstore or library with child, parents talk with child about what he/she is reading.

[15] Appendix Table B2 presents the standardized coefficients, with variables standardized to have a mean of 0 and a standard deviation of 1.

Table 1: Correlates of the SES gradient in learning

	SES gradient in math							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita	-1.901							-1.528
	(1.432)							(1.379)
Returns to secondary school		0.285*						0.012
		(0.137)						(0.102)
Difference between top and lowest tax rates on personal income			-0.051					0.048
			(0.072)					(0.053)
Government expenditure on education (% of GDP)				-0.498				0.979
				(0.569)				(0.563)
School tracking age					-0.987***			-1.074**
					(0.319)			(0.456)
School segregation						38.118***		1.775
						(10.741)		(15.890)
SES gradient in parental investment							0.841***	0.532**
							(0.128)	(0.202)
Observations	24	22	23	23	23	23	24	20
R^2	0.090	0.193	0.034	0.020	0.369	0.352	0.570	0.741

Note. The table shows the estimates from the SES gradient in math (averaged over all PISA years) and country-level variables (averaged over all PISA years). We consider different sets of variables. Some are socio-economic variables: the returns to secondary school from the OECD, country GDP. Some are institutional variables, such as the progressivity of the tax system, proxied by the difference between top and lowest tax rates on personal income, and spending in public education. Some are related to the education system, such as the age in which academic tracking starts, from Eurydice and school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

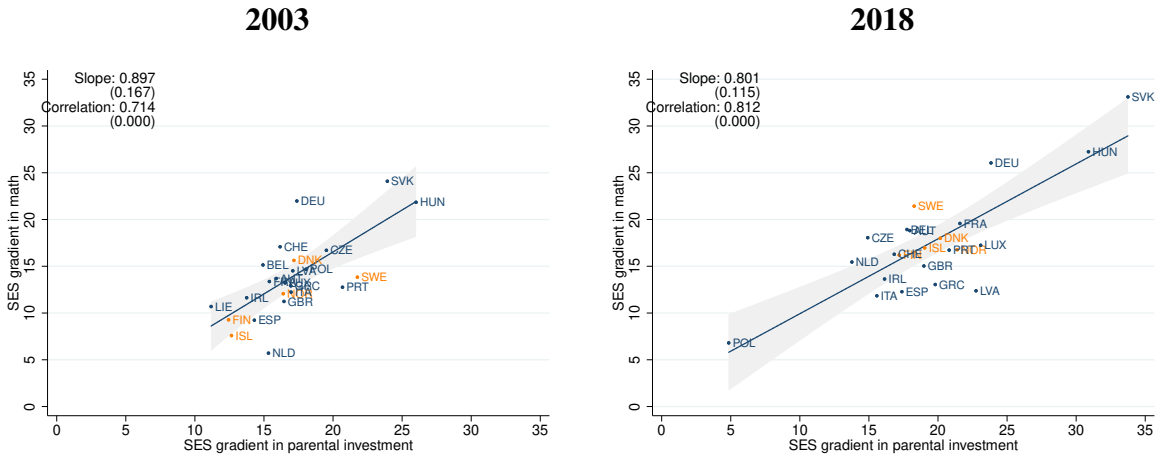
starts early, such as in the case of Germany, would provide fewer chances for disadvantaged students to escape the least academic tracks, leading to larger SES gradients in test scores. In addition, a stronger sorting of students to schools based on SES (a higher level of SES segregation in schools) could lead to lower social mobility, especially if high-SES schools are also better schools (because they are better equipped, have better teachers, or because students have higher achieving peers).

The fact that there is a strong relationship between SES gradients in learning and SES gradients in parental investments is also not surprising, especially if the parental investment index we construct is a powerful predictor of an individual's test scores.[16] What is perhaps noteworthy is the strength of this association. Figure 4 plots SES gradients in learning and SES gradients in parental investment for two PISA cohorts: 2003 and 2018. The correlation between these two variables is 0.71 in 2003 and 0.81 in 2018, both of which are strikingly high values.

Interestingly, Nordic countries, highlighted in orange in Figure 4, do not have particularly high or low SES gradients in parental investments. While in 2003, Finland and Iceland had values for these gradients that were among the lowest in Europe (which was not the case for Denmark, Norway, or Sweden); by 2018, their values are indistinguishable from the typical European country, even though the quantity and quality of public services available to disadvantaged children may be especially high in these countries. On top of that, more advantaged

[16]We also compute bootstrapped standard errors with 50 iterations to account for uncertainty in the generated regressors (i.e., SES gradient for test scores and parental investment). Since the bootstrapped procedure produces standard errors similar to the robust method (bootstrapped SE: 0.042) and is computationally demanding, we compute bootstrapped standard errors only for the relationship between SES in test scores and parental investment.

Figure 4: Correlation between SES gradients in math and SES gradients in parental investment.



Note. The figures present the correlation between the SES gradient in learning (math) and SES gradients in parental investment. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

parents are still able to invest more in their children than less advantaged parents, and the degree to which they do so is as high in Nordic countries as anywhere else. Therefore, it is perhaps not surprising that SES gradients in PISA scores are not especially low in Nordic countries.

We also conduct a battery of robustness checks for the relationship between SES gradients in learning and SES gradients in parental investment. First, Appendix Table B3 shows that this relationship is robust to excluding one country at a time. Second, Appendix Table B4 shows that the association between the SES gradient in learning outcomes and the SES gradient in parental investment remains robust, when controlling for compositional factors, such as the percentage of migrant students and the percentage of mothers with less than a high school education. Third, we show that this relationship is robust to using the other measures of intergenerational transmission of learning described in the Appendix (Appendix Table B5). Specifically, Appendix Table B5 reproduces Columns (7) and (8) of Table 1 using the other measures of intergenerational transmission of l learning.

We finally attempt to search for potential predictors of SES gradients in parental investment, at least in the cross section. Two variables, related to social norms and attitudes towards education, are correlated with SES gradients in parental investment: (i) confidence in the education system from the 2017 European Value Study (EVS), and (ii) perception that success depends strongly on parental wealth from the 2009 International Social Survey Programme (ISSP). The left panel of Appendix Figure B10 shows that a higher confidence in the education system is negatively correlated with larger socio-economic gradients in parental investment, while the right panel of Appendix Figure B10 shows that a stronger belief in the importance of a wealthy background is positively correlated with larger socio-economic gradients in parental investment.

4.3.2 Panel analysis

The cross-sectional associations, reported in the previous section, are interesting but they are also difficult to interpret because they may be driven primarily by third factors. Although we are not able to convincingly estimate the causal impact of these variables on social mobility in learning, we can nevertheless examine if changes over time/across cohorts in at least some of these variables are correlated with changes over time/across cohorts in SES gradients in PISA scores. This is possible because we observe multiple cohorts of children taking the PISA in multiple countries, between 2003 and 2018.

We therefore estimate the following model:

$$\beta_{tc}^{math} = X_{tc}\gamma + \tau_t + \theta_c + \epsilon_{tc} \tag{2}$$

where β_{tc}^{math} is the SES gradient in math for country c and cohort t, and X_{tc} is a country- and time-varying variable of interest. We include the year fixed effects, τ_t, and country fixed effects, θ_c, and ϵ_{tc} is the residual. We cluster standard errors at the country level. We also report bootstrapped standard errors based on 50 repetitions to incorporate the uncertainty in the estimated SES gradient in test scores and parental investment. Importantly, we find that the bootstrapped standard errors are similar to the cluster robust standard errors. Given the computational intensity of this process and the similarity of estimates standard errors, we bootstrap only the relationship between SES in test scores and SES in parental investment.

The parameter of interest is γ and the estimates for all variables are available in Table 2. Here we would like to focus on the three main predictors of SES gradients in test scores: tracking age, school segregation, and SES gradients in investments. We cannot really use tracking age in this model because there are little to no changes in this variable across countries during the period we study. Therefore, we present results only for the other two variables.

Columns (5) and (6) of Table 2 document that changes in how segregated schools are across cohorts are not correlated with changes in SES gradients in PISA scores, but changes in SES gradients in parental investments are strongly related to changes in SES gradients in PISA scores.[17] If we regress SES gradients in PISA scores on all the country- and time-varying variables, considered in Table 2, the SES gradients in parental investment survive and remain statistically significant with a similar magnitude (Column (7)).[18]

Figure 5 shows graphically the relationship between SES gradients in PISA scores and SES gradients in parental investment by plotting changes in SES gradients in PISA scores between 2003 and 2018 against changes in SES gradients in investment (left panel) and changes in segre-

[17] The bootstrapped standard errors for the relationship between changes in SES gradients in parental investments and changes in SES gradients in PISA scores is 0.067.

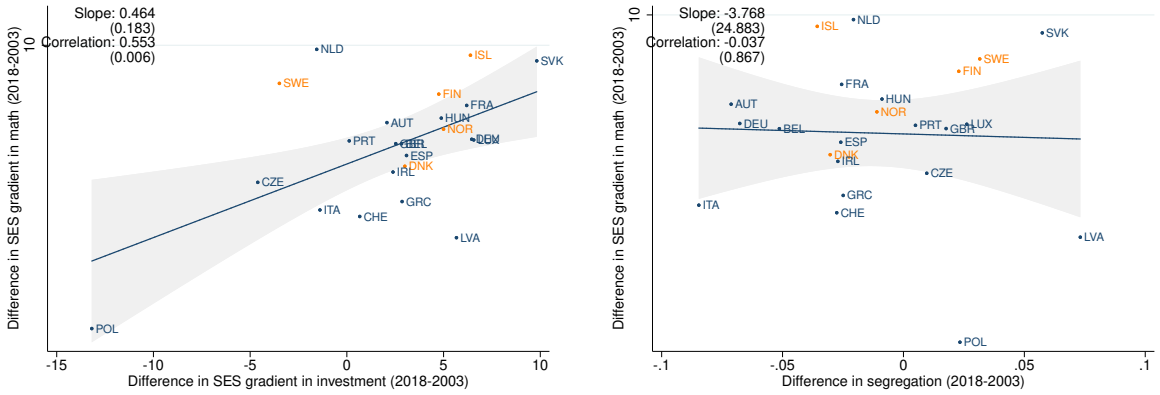
[18] Appendix Table B6 presents the standardized coefficients, with variables standardized to have a mean of 0 and a standard deviation of 1.

Table 2: Panel regressions: SES gradient in test scores

	SES gradient in math						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	-1.477						-5.149
	(4.119)						(5.433)
Returns to secondary school		0.106*					0.051
		(0.053)					(0.086)
Difference between top and lowest tax rates on personal income			0.028				0.083
			(0.066)				(0.110)
Government expenditure on education (% of GDP)				-0.342			-0.354
				(0.565)			(0.563)
School segregation					7.840		2.549
					(11.276)		(15.906)
SES gradient in parental investment						0.564***	0.631***
						(0.129)	(0.189)
Observations	160	118	137	117	159	142	74
R^2	0.802	0.841	0.808	0.819	0.802	0.881	0.916
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the panel estimates of the SES gradient in learning on economic variables with year and country fixed effects (equation (2)). The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Figure 5: Correlation: changes in SES gradients in learning, SES gradients in investment and segregation between 2003 and 2018.



Note. The figure presents the correlation between the changes in SES gradients in learning (math), changes in the socio-economic gradients in parental investment, and changes in segregation between 2003 and 2018. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The rank is computed at the European level. Segregation is measured in the PISA data as the R-squared from regressing the ESCS index on school fixed effects. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

gation (right panel) during the same period. Strikingly, the countries, that have experienced the largest increase in the gradients in parental investments between more and less advantaged families, are Nordic countries: Norway, Finland, Iceland and Denmark. These results are, however, not driven by changes in inequality in these countries. We indeed show that there is no strong correlation between inequality in ESCS and SES gradients in parental investments (Appendix Figure B9). Additionally, as we show in Section 4.1, income inequality is not correlated with SES gradients in the PISA scores.

There could be several potential drivers of SES gradients in PISA scores. For example,

the provision of public standardized education services, and the degree of inequality in school quality between schools attended by poor and rich students could in theory play a big role. In practice, we do not find evidence that this is the case. Although we see that the degree to which students segregate into schools based on their SES is associated with SES gradients in learning in the cross section, we do not find such relationship when we look at the panel.

We finally conduct a battery of robustness checks for the panel relationship between SES gradients in learning and SES gradients in parental investment. First, Appendix Table B7 shows that this relationship is robust to excluding one country at a time. Second, Appendix Table B8 shows that the association between the SES gradient in learning and the SES gradient in parental investment remains robust, when controlling for compositional factors, such as the percentage of migrant students and the percentage of mothers with less than a high school education. Third, we show that this relationship is robust to using the other measures of intergenerational transmission of l learning described in the appendix (Appendix Table B9 reproduces Columns (6) and (7) of Table 2 using the other measures of intergenerational transmission of l learning).

It is therefore interesting that the main driver of the differences in SES gradients in PISA scores across countries seems to be differences in SES gradients in parental investment in children. Although we cannot rule out that whatever factors driving differences in SES gradients in parental investments across countries or time also have an independent effect on SES gradients in PISA scores, it is interesting to think about what these factors may be. In sum, our results suggest that the roots of inequality in child outcomes lie in the family, despite equalizing policies, such as those observed in Nordic countries, aimed at levelling the playing field.

4.4 Upward mobility

There are many measures of social mobility, and one that has become very prominent is upward mobility (e.g., Chetty et al. (2014); Deutscher and Mazumder (2023)). Upward mobility measures the average outcomes of individuals coming from a disadvantaged background. In our setting in particular, this corresponds to the average rank in the PISA score distribution for individuals whose mothers have less than upper secondary schooling. It is of substantial interest if one is particularly worried about the outcomes of the most disadvantaged groups in a given country.

This is a very different measure from the one we focused on so far, and it may vary across countries for different reasons. For example, a country with an excellent education system can make sure the poor have good learning levels, without changing the gradients between learning levels of poor and rich students. In fact, it is remarkable how large the differences across countries in this measure are.

For example, in 2003, low-SES students in the Netherlands or Finland perform well above the 55^{th} percentile of the distribution of PISA across all countries, while in Greece, Hungary or

Slovakia such students perform below the 30^{th} percentile. By 2018 the test scores of low-SES students decreased substantially across the board. They score in the 44^{th} and 38^{th} percentiles in the Netherlands and Finland respectively, and in the 25^{th}, 21^{st} and 16^{th} percentiles in Greece, Hungary and Slovakia. It is also striking that the average student, whose mother has less than an upper secondary education, in countries, such as Finland or Iceland, has higher PISA scores than the average students, whose mothers have completed at least upper secondary, in countries, such as Italy or Portugal.

Upward mobility and the average PISA score of students in a country are obviously correlated, but far from perfectly (Appendix Figure C1): these patterns are not just explained by average differences across countries. For this reason, when we explore the correlates of the SES gradient in learning, we do not observe the same patterns as the ones noted by Woessmann (2016). In addition, perhaps unsurprisingly, the ranking of countries with regard to upward mobility is not exactly the same as the ranking using the SES gradient in learning, but there is a strong correlation of 0.60 in 2003 and 0.80 in 2018 (Appendix Figure C2).

Regarding the correlates of upward mobility, they work as the correlates of the SES gradient in learning. There is no correlation with inequality across countries or over time, and in the cross section, school segregation, age at first tracking, and SES gradients in parental investments have the strongest correlations with upward mobility in learning. In the panel, once we control for country and cohort fixed effects, only changes in the SES gradients in parental investment remain an important predictor of changes in upward mobility within country and over time (Appendix Table C1).

4.5 SES gradients in other traits

PISA has rich information on child outcomes, which we can use to examine SES gradients in learning and traits more broadly. First, there are the well-known PISA scores, not only in math, but also in reading and science. Second, there are measures of occupational and educational aspirations for each child. Third, there are measures of self-efficacy and being on time to school. We describe these measures below and refer to Appendix C.3 for further details.

It is important, to the extent possible, to look beyond SES gradients in one academic subject, as human capital is multi-dimensional (see, for example, Heckman et al. (2006) and Deming (2023)). To measure students' educational and occupational aspirations, we follow La Ferrara (2019), defining occupational aspiration with a dummy equal to 1 for students, who expect to have a white collar job, and educational aspiration with a dummy equal to 1 for students, who expect to study at university. Self-efficacy captures the extent to which individuals believe in their own ability to engage in certain activities and perform specific tasks, especially when facing adverse circumstances (Bandura, 1977, 1991). To measure non-cognitive skills, we look at the probability of being on time to school (Cunha and Heckman, 2007; Borghans et al., 2008).

We measure the SES gradient and upward mobility in these other traits by estimating equation (1), where the outcome is now one of the traits we describe above. Upward mobility is then the average trait for the children whose mothers have not completed upper secondary education. The SES gradient in the trait is instead the difference in a certain trait between children whose mothers have completed at least upper secondary and mothers that have not.

We begin by showing how correlated (within a given year) measures of mobility using different traits are. Table 3 shows the matrix of correlations for SES gradients in learning in 2018 (the remaining years, and correlations for upward mobility measures, are available in Appendix Tables C2 and C3).

As expected, it makes very little difference to measure SES gradients in math, reading or science. SES gradients in aspirations have strong positive correlations with SES gradients in test scores, but which are substantially away from 1, suggesting that these are quite different traits. Still positive, but less correlated with SES gradients in test scores, are SES gradients in being on time to school. Similar patterns are also found for the SES gradients in self-efficacy, which is available for 2003 and 2012 (Appendix Figure C3).

Table 3: Correlation among SES gradients (2018)

	SES gradient in					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.962***	1				
Science	0.963***	0.980***	1			
Educational aspiration	0.473**	0.367*	0.345	1		
Occupational aspiration	0.541***	0.386*	0.361*	0.766***	1	
Being on time to school	0.536***	0.565***	0.571***	-0.047	-0.015	1

Note. The table presents the correlation among different measures of the SES gradient in learning for 2018. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Interestingly, Nordic countries experience low mobility - not only in learning outcomes - but also in these other traits. More importantly, we still uncover a strong relationship between SES gradients in these other traits and the SES gradients in parental investment, while we do not find a correlation between SES gradients in these other traits and inequality (Appendix Table C4).

5 SES gradients in learning before and after COVID-19

We also explore the recently-released PISA data from the 2022 wave and compare SES gradients in test scores in 2018 and 2022 (i.e., before and after the COVID-19 pandemic). Although it could be tempting to attribute any changes to the experience of students during the pandemic, there are longer-term trends in these gradients that should be considered first. This section focuses on the SES gradients in test scores, while other studies have documented a decrease in the average scores and in the share of students who are able to reach a minimum competence (e.g., European Commission (2024)).

From the 2022 data, we still observe that SES gradients in test scores are as high for the Nordic countries as for the remainder of the countries in the sample (Appendix Figure D1). Appendix Figure D2 shows that there is a strong correlation between SES gradients in math scores in 2018 and 2022, and that the level of these gradients has not changed significantly between these two years. This can also be observed in Appendix Figure D3, presenting the trends in the SES gradient in learning and upward mobility across several countries, with the 2022-PISA wave. Although it is true that there are several countries for which the SES gradient in PISA scores reached its highest value in 2022, there are also many others where this is not the case. More importantly, there is no obvious change in the evolution of these gradients over time. For most if not all countries, the 2022 data seem to follow a trend, rather than exhibiting a break from the past. Such patterns are also observed when we examine the evolution of SES gradients in parental investments between 2018 and 2022 (Appendix Figure D4).

We also continue to see a strong correlation between SES gradients in parental investment and SES gradients in test scores, while we find no correlation between school closures during COVID-19 and SES gradients in test scores. In fact, comparing Appendix Figure D5 with Figure 4, we see that, if anything, the relationship between SES gradients in parental investment and SES gradients in test scores becomes stronger (correlation: 0.89). On the other hand, Appendix Figure D6 documents a lack of correlation between the number of fully-closed school days due to COVID-19 in lower secondary education in 2020 (a proxy for public investment) from OECD (2021) and SES gradients in test scores in 2022 (correlation: 0.07). These results suggest that the COVID-induced disruption in learning, and more generally, in economic and social environments, experienced by children and their families, has not produced substantial changes in the patterns studied in this paper.

6 Conclusion

Standardized international tests show significant differences in student knowledge across countries, even within Europe. Not only that, there are also staggering differences in the magnitude

of SES gradients in test scores across countries, in the test performance of the most disadvantaged students in each country, and how these vary over time.

Take the case of PISA, which is the main data source for our paper. In 2003, the gradients in PISA scores between children, whose mothers have or have not completed at least upper secondary education, are (to give just a few examples) 5 percentile ranks in the Netherlands, 11 in Great Britain, 16 in Denmark, and 22 in Germany. Fast forward to 2018, and these values are respectively, 16, 15, 18 and 26. A similar picture is found for upward mobility, where we observe a decline of the average performance of disadvantaged students.

It is interesting that in Nordic countries, with generous and universal social benefits, SES gradients in learning are not particularly low, when compared to other European countries. This is especially true for the most recent cohorts of PISA, and generalizes the findings by Landerso and Heckman (2017) and Heckman and Landerso (2022), comparing Denmark and the USA. In fact, there is no correlation between the SES gradients in PISA scores and inter/intra-generational income inequality, neither in the cross section nor the time series. PIAAC data suggest that this may have *not* been the case in the past.

Finally, when investigating the main correlates of SES gradients in PISA scores, we find them to be correlated with the level of SES segregation in schools, the age at which tracking first starts in the education system, and the SES gradients in parental investments. Of these, only the latter shows a cross-sectional association that persists even when we consider the entire panel and account for country and time fixed effects.

These findings suggest that while social policies contribute to addressing SES gradients in learning, family behaviors still play an important role in perpetuating these gaps. If other countries were to import the same type of education and social policies as Nordic countries, it is not clear that they would experience substantial reductions in SES gradients in learning. These findings also suggest alternative policies, such as opening up bottlenecks along the path to success, to break the intergenerational transmission of inequality (Fishkin, 2014; Durlauf et al., 2024). For example, to the extent that test scores are a good predictor of enrolment in elite universities, which are conducive to top jobs, easing bottlenecks at these institutions could expand access to opportunities and mitigate inequalities.

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Appendices to "Parental Investments and Socio-Economic Gradients in Learning across European Countries"

A Descriptive evidence

Table A1: Mapping of three-letter country codes to full country names

Country Code	Full Country Name
AUT	Austria
BEL	Belgium
CHE	Switzerland
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
FIN	Finland
FRA	France
GBR	United Kingdom
GRC	Greece
HUN	Hungary
IRL	Ireland
ISL	Iceland
ITA	Italy
LIE	Liechtenstein
LUX	Luxembourg
LVA	Latvia
NLD	Netherlands
NOR	Norway
POL	Poland
PRT	Portugal
SVK	Slovakia
SWE	Sweden

A.1 Data validation of mother's education and ESCS index

Answers on parental education were coded by PISA into internationally-comparable educational qualifications, following the international Standard Classification of Education (ISCED), presented in Appendix Table A2.

Panel A of Appendix Figure A1 presents the correlation between the proportion of mothers with at least upper secondary education (average over 7 PISA waves) and the proportion of females (aged 25+) with at least upper secondary education (World Bank database).

We note that the proportion of mothers with at least upper secondary education is higher than proportion of females (aged 25+) with at least upper secondary education from the World Bank. This is because in PISA we have mothers, while in the World Bank we have the female population. The correlation between the two is however high - close to 0.90.

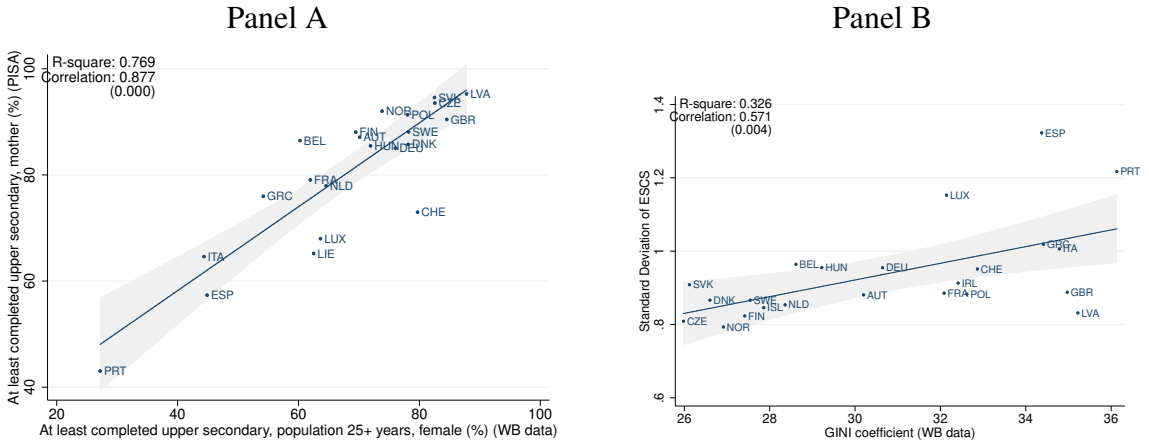
Table A2: International Standard Classification of Education (ISCED) levels

Level	ISCED
0	None
1	ISCED 1 (primary education)
2	ISCED 2 (lower secondary)
3	ISCED Level 3B or 3C (vocational/pre-vocational upper secondary)
4	ISCED 3A (upper secondary) and/or ISCED 4 (non-tertiary post-secondary)
5	ISCED 5B (vocational tertiary)
6	ISCED 5A, 6 (theoretically oriented tertiary and post-graduate)

Note. The table presents the International Standard Classification of Education (ISCED) classification. PISA codes the answers on parental education into internationally-comparable educational qualifications, following the international Standard Classification of Education (ISCED).

Panel B of Appendix Figure A1 presents the correlation between the standard deviation of the PISA index of economic, social and cultural status (ESCS) and the Gini coefficient from the World Bank.

Figure A1: Correlation between PISA and the World Bank data



Note. Panel A presents the correlation between the proportion of mother with at least upper secondary education in PISA and the proportion of females (aged 25+) with at least upper secondary education in the World Bank database. Panel B presents the correlation between the standard deviation of the ESCS index in PISA and the Gini coefficient from the World Bank. In each panel, we compute each statistics at the country level for each wave and then link it to the respective wave of the World Bank database. The figures present the correlation between the averages computed over the 7 PISA waves. Confidence interval at 95% level in gray. The notes in the figures report the R-squared and the correlation between variables with the p-value in parenthesis.

A.2 Descriptive statistics on leaning mobility

Table A3: Descriptive statistics on leaning mobility

Country	Upward	SES gap	Upward	SES gap	Upward	SES gap	Upward	SES gap	Upward	SES gap	Upward	SES gap	Upward	SES gap
	2000		2003		2006		2009		2012		2015		2018	
AUT	49.17	10.53	41.04	13.69	38.60	17.58	32.25	19.95	34.43	20.64	31.07	22.45	34.65	18.82
BEL	44.90	20.18	49.75	15.14	44.27	18.47	42.71	17.31	39.07	20.08	38.10	18.89	37.84	18.93
CHE	50.35	18.68	47.77	17.08	50.50	15.50	49.05	16.91	47.13	17.40	44.05	18.32	43.11	16.28
CZE	35.89	16.19	41.33	16.70	31.39	25.14	31.39	18.56	32.71	18.99	35.77	15.78	35.53	18.06
DEU	30.11	25.76	38.68	21.98	38.47	20.77	41.39	20.28	30.74	29.18	33.13	24.76	30.90	26.05
DNK	43.94	16.67	43.01	15.62	44.61	14.00	39.11	15.99	36.80	16.81	43.30	14.90	37.71	17.99
ESP	39.56	14.11	41.81	9.24	40.82	11.31	39.94	11.57	38.57	12.81	39.55	12.52	37.18	12.28
FIN	57.59	7.53	56.37	9.28	58.85	9.51	51.42	13.85	44.44	13.99	39.91	16.39	38.42	16.19
FRA	49.58	12.12	45.65	13.37	40.21	16.34	37.43	18.99	35.01	19.56	34.80	18.94	33.48	19.58
GBR	50.32	13.91	44.25	11.24	41.80	11.55	35.88	16.07	37.80	14.50	36.54	15.55	39.25	15.03
GRC	29.12	15.22	26.23	12.91	29.40	14.91	30.76	13.35	25.46	14.20	26.03	13.62	25.11	13.05
HUN	29.80	22.15	29.23	21.84	30.12	22.57	25.66	27.37	23.74	24.51	21.46	26.87	21.38	27.25
IRL	46.91	9.89	42.81	11.63	42.76	12.98	39.37	11.37	42.27	11.02	40.44	13.90	38.83	13.64
ISL	51.71	9.64	50.45	7.59	45.30	12.68	43.51	13.59	40.71	10.92	38.24	11.87	35.58	16.96
ITA	34.50	9.13	33.42	12.23	34.44	10.76	39.79	10.23	38.47	11.81	40.16	12.28	38.76	11.84
LIE	52.11	14.64	55.19	10.70	51.23	13.43	48.41	20.14	49.79	14.83				
LUX	32.58	10.75	40.89	13.21	40.79	13.76	36.82	17.88	35.84	18.41	35.34	17.21	34.18	17.24
LVA	28.72	14.36	31.47	14.52	33.03	15.58	36.67	9.17	33.34	15.67	31.95	14.66	38.17	12.38
NLD	67.79	8.02	60.15	5.71	53.66	10.41	48.61	13.28	51.18	9.12	44.57	12.88	44.17	15.45
NOR	46.24	7.60	38.70	12.07	37.26	13.49	38.70	13.06	35.98	13.68	38.08	15.62	36.54	16.77
POL	38.71	6.80	33.65	14.68	34.57	17.49	32.94	18.26	36.98	20.24	47.33	6.73	50.01	6.80
PRT	35.28	11.88	35.92	12.76	36.80	14.89	39.72	18.57	40.18	17.68	40.94	16.86	39.87	16.73
SVK			27.84	24.09	24.14	27.49	22.74	28.40	15.60	32.11	17.85	28.76	16.36	33.11
SWE	47.35	9.50	42.66	13.83	41.81	13.38	35.18	17.42	32.87	14.30	31.55	21.36	33.69	21.43

Note. The table presents the estimates of the SES gradient and upward mobility. The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of the SES gradient in learning correspond to lower mobility.

A.3 Robustness to alternate measures

Appendix Table A4 shows that the correlation between the alternate measures is relatively high, providing confidence that the main results are robust to different definitions of intergenerational transmission of learning.

Reading test score - we estimate the intergenerational transmission of learning (1) by using the rank of the reading test score.

Rank at country level - we estimate the intergenerational transmission of learning (1) by using the rank of the test score at the country level. The country rank is constructed by ordering the each plausible value of the test scores in ascending order within each country, using the weights provided by PISA. By defining within-country ranks, the estimated social mobility parameter compares the positions in the country's outcome distribution of children at different points of the country's SES distribution. The disadvantage of this measure is the difficulty in comparing estimates across countries, since the distribution of test scores may vary considerably from country to country. We note that constructing a European rank may be problematic if the test score distributions do not overlap across countries. Appendix Tables A5 and A6, however, show a good overlap of the test score distribution across countries.

Alternate measures of parental socio-economic status.

Father's education - we compute the main measure of SES gradient in learning in math from equation (1) by using the father's education dummy, instead of the mother's ($\beta_{tc}^{math-father}$).

Mother's higher education - we define an indicator variable taking value 1 if i's mother has completed higher education (HE^P_{itc}), and 0 otherwise (Appendix Table A2). For each student i, country c, cohort t and subject k, we estimate:

$$R(Y^k_{itc}) = \alpha^{k-uni}_{tc} + \beta^{k-uni}_{tc} HE^P_{itc} + \epsilon^k_{itc} \tag{3}$$

Rank of ESCS - we estimate a rank-rank regression, where we regress the rank of the math test score on the rank of the socio-economic and cultural status (ESCS), which can be considered as a proxy of permanent income. For each student i, country c, cohort t and subject k, we estimate:

$$R(Y^k_{itc}) = \mu^k_{tc} + \rho^k_{tc} R(Y^P_{itc}) + \epsilon^k_{itc} \tag{4}$$

where $R(Y)^k_{itc}$ is test score (rank) for subject k for student i at time t living in country c and $R(Y)^p_{itc}$ is i's the index of socio-economic and cultural status (rank). The index of socio-economic and cultural status (ESCS) is derived from three factors: highest parental occupation, highest parental education, and an Item response Theory (IRT) scale based on student reports on home possessions. PISA has constructed the index in 2015, making it comparable over the waves. ESCS components and the ESCS model has changed over cycles and with that, ESCS scores are not comparable across cycles directly. To enable a trend study, PISA 2015 computes the ESCS measure for the 2015 cycle and also recomputes it for the earlier cycles using the same methodology.[2]

Above median education - we use a different definition of socio-economic status by defining the indicator variable taking value 1 if i's mother has at least the median education within the country (ME^P_{itc}), and 0 otherwise. For each student i, country c, cohort t and subject k, we estimate:

$$R(Y^k_{itc}) = \alpha^{k-med}_{tc} + \beta^{k-med}_{tc} ME^P_{itc} + \epsilon^k_{itc} \tag{5}$$

where β^{k-med}_{tc} is difference in math rank between children whose mothers have below and at least the median education within the country and α^{k-med}_{tc} is the children's average rank when the mother has below the median education within the country.

[2]Some example of changes over the different waves are the following. The mapping of ISCED levels to years of schooling was updated in 2009 and 2015 for some countries, taking into account changes in countries' learning systems. Indicators of home possession (HOMEPOS) have been dropped or added in all PISA cycles (except in PISA 2012) taking into account social, technical and economic changes in participating societies. Moreover, the method for HOMEPOS estimation has changed in PISA 2009, PISA 2012 and PISA 2015. Since PISA 2012 parental occupation is coded into HISEI using the current international standard classification of occupations, ISCO-08. Previous cycles used ISCO-88. For the effects of ISCO-08 compared to ISCO-88 on ESCS and performance please see PISA 2012 Technical Report, pp. 372 (OECD, 2014).

Table A4: Correlation among alternate intergenerational transmission of learning measures

	Relative mobility						
	β_tc^{math}	$\beta_tc^{math-father}$	β_tc^{math-c}	β_tc^{read}	$\beta_tc^{math-uni}$	$\beta_tc^{math-med}$	ρ_tc^{math}
β_tc^{math}	1						
$\beta_tc^{math-father}$	0.942***	1					
β_tc^{math-c}	0.992***	0.928***	1				
β_tc^{read}	0.973***	0.941***	0.957***	1			
$\beta_tc^{math-uni}$	0.337	0.405*	0.342	0.292	1		
$\beta_tc^{math-med}$	0.714***	0.784***	0.701***	0.678***	0.739***	1	
ρ_tc^{math}	0.763***	0.753***	0.711***	0.772***	0.376*	0.661***	1

	Upward mobility						
	α_tc^{math}	$\alpha_tc^{math-father}$	α_tc^{math-c}	α_tc^{read}	$\alpha_tc^{math-uni}$	$\alpha_tc^{math-med}$	μ_tc^{math}
α_tc^{math}	1.000						
$\alpha_tc^{math-father}$	0.967***	1.000					
α_tc^{math-c}	0.670***	0.652***	1.000				
α_tc^{read}	0.888***	0.911***	0.774***	1.000			
$\alpha_tc^{math-uni}$	0.686***	0.621***	0.007	0.399*	1.000		
$\alpha_tc^{math-med}$	0.852***	0.866***	0.248	0.668***	0.861***	1.000	
μ_tc^{math}	0.737***	0.706***	0.362*	0.644***	0.625***	0.632***	1.000

Note. The table presents the correlation among different measures of intergenerational transmission of learning (averaged across PISA waves). "β_{tc}^{math}" is the main measure of the SES gradient in learning in math from equation (1), $\beta_{tc}^{math-father}$ is the main measure of the SES gradient in learning in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of the SES gradient in learning in reading from equation (1), β_{tc}^{math-c} is the SES gradient in learning in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is the SES gradient in learning in math from equation (3), $\beta_{tc}^{math-med}$ is the SES gradient in learning in math from equation (5), ρ_{tc}^{math} is the SES gradient in learning from equation (4) using the rank of the parents' ESCS.
α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. (*** p<0.01, ** p<0.05, * p<0.1).

A.4 Descriptive statistics on test scores

Table A5: Test score statistics, 2003

Country Name	Reading							Mathematics						
	Min	P25	P50	P75	Max	Mean	N	Min	P25	P50	P75	Max	Mean	N
AUT	16.62	423.47	498.69	565.05	786.68	490.69	4597	205.42	439.37	506.22	571.43	790.92	505.61	4597
BEL	31.54	439.93	521.61	587.04	792.17	506.99	8796	114.3	456.22	537.14	611.17	834.06	529.29	8796
CHE	96.51	438.52	505.98	565.28	787.34	499.12	8420	164.42	460.76	529.66	594.98	839.12	526.55	8420
CZE	160.17	427.78	494.53	555.26	800.9	488.54	6320	199.41	449.4	516.77	584.41	857.83	516.46	6320
DEU	69.23	418.51	503.62	571.75	782.91	491.36	4660	147.31	432.17	509.16	578.31	801.06	502.99	4660
DNK	86.67	437.75	498.47	553.38	760.64	492.32	4218	157.36	453.17	516.08	578.24	777.16	514.29	4218
ESP	7.39	420.5	486.99	548.19	756.96	480.54	10791	115.42	426.19	487.1	546.44	787.38	485.11	10791
FIN	152.82	493.63	549.2	598.78	803.6	543.46	5796	223.15	488.24	543.73	602.63	837.64	544.29	5796
FRA	119.61	436.03	504.99	565.43	757.01	496.19	4300	189.7	449.06	514.24	575.25	782.94	510.8	4300
GBR	106.88	445.47	511.87	573.58	809.24	507.01	9535	146.8	444.1	509.78	572.6	808.9	508.26	9535
GRC	-17.89	406.34	479.84	545.95	780.09	472.27	4627	77.85	382.36	446.11	507.87	768.66	444.91	4627
HUN	129.4	422.03	486.57	546.47	752.47	481.87	4765	153.86	426.09	489.97	555.88	794.66	490.01	4765
IRL	150.09	460.18	520.64	576.9	754.22	515.48	3880	203.47	444.99	503.47	561.88	789.53	502.84	3880
ISL	53.3	430.74	498.6	560.3	789.42	491.75	3350	187.09	454.23	518.21	578.44	806.62	515.11	3350
ITA	-8.97	411.36	483.43	547	873.68	475.66	11639	68.09	400.47	466.07	530.24	817.56	465.66	11639
LIE	250.65	467.06	529.87	588.42	725.95	525.08	332	222.67	469.86	539.2	608.6	799.88	535.8	332
LUX	57.92	415.74	488.15	551.42	742.46	479.42	3923	180.11	430.24	495.23	557.17	793.86	493.21	3923
LVA	119.81	430.95	494.94	554.26	782.02	490.56	4627	140.22	423.52	484.06	543.53	811.51	483.37	4627
NLD	204.49	454.11	516.93	576.14	759.73	513.12	3992	213.24	470.95	539.62	608.32	802.41	537.82	3992
NOR	47.28	434.25	507.11	570.56	813.38	499.74	4064	179.75	432.87	495.26	559.99	814.57	495.19	4064
POL	106.47	436.43	500.46	562.63	799.43	496.61	4383	136.97	428.2	489.67	552.81	776.63	490.24	4383
PRT	126.46	417.62	485.57	543.81	753.32	477.57	4608	170.06	405.97	467.18	526.14	751.77	466.02	4608
SVK	54.77	407.86	472.68	535.3	751.61	469.16	7346	115.78	435.55	498.33	564.59	825.27	498.18	7346
SWE	34.53	453.14	520.57	581.58	803.7	514.27	4624	117.85	446.08	509.6	575.57	799.64	509.05	4624

Note. The table presents the descriptive statistics on the reading and math test scores in 2003.

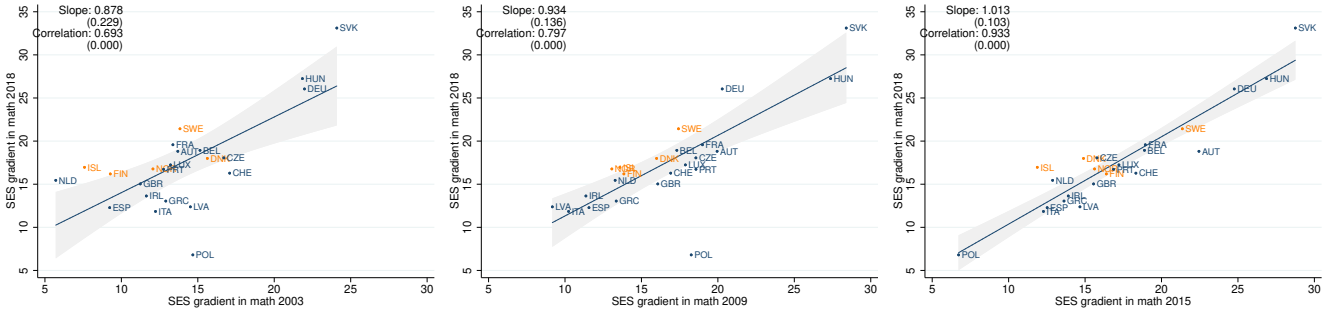
Table A6: Test score statistics, 2018

Country Name	Reading							Mathematics						
	Min	P25	P50	P75	Max	Mean	N	Min	P25	P50	P75	Max	Mean	N
AUT	163.36	412.73	488.16	557.72	771.94	484.39	6802	166.55	433.41	503.24	566.41	785.17	498.94	6802
BEL	145.69	421.39	497.6	567.82	801.94	492.86	8475	186.05	439.83	514.23	578.98	801.67	508.07	8475
CHE	70.28	412.76	488.08	557.74	796.57	483.93	5822	172.3	447.98	518.06	582.1	822.22	515.31	5822
CZE	164.68	422.06	491.61	559.9	804.6	490.22	7019	172.98	434.99	501.02	564.29	819.13	499.47	7019
DEU	164.65	424.21	503.81	575.87	836.03	498.28	5451	179.76	433.05	504.05	569.71	803.27	500.04	5451
DNK	130.35	438.56	504.41	566.12	791.55	501.13	7657	191.78	453.69	511.51	567.45	771.37	509.4	7657
ESP	147.93	413.24	479.21	542.51	799.77	476.54	35943	127.47	420.99	484.37	544.24	808.4	481.39	35943
FIN	145.86	455.09	526.9	591.18	823.9	520.08	5649	178.6	451.33	510.43	564.74	776.51	507.3	5649
FRA	139.57	422.89	496.94	566.62	807.17	492.61	6308	151.59	432.93	501.72	562.21	775.73	495.41	6308
GBR	160.47	435.36	506.3	574.83	846.54	503.93	13818	122.58	438.72	503.78	566.71	813.21	501.77	13818
GRC	157.19	390.2	459.73	526.46	771.41	457.41	6403	127.59	390.6	453.55	513.26	758.55	451.37	6403
HUN	180.88	406.69	479.06	547.24	776.83	475.99	5132	148.92	417.89	484.03	546.03	771.87	481.08	5132
IRL	207.82	456	519.95	582.64	797.02	518.08	5577	219.19	447.49	502.06	553.79	743.68	499.63	5577
ISL	163.82	402.48	477.44	549.44	795.8	473.97	3296	194.88	433.9	499.3	558.55	767.23	495.19	3296
ITA	142.5	413.14	481.34	544.63	785.98	476.28	11785	154.72	423.35	490.24	551.97	791.6	486.59	11785
LUX	153.3	392.36	471.54	547.95	804.29	469.99	5230	162.42	412.86	485.37	554.8	790.08	483.42	5230
LVA	170.92	415.21	480.49	542.35	775.1	478.7	5303	211.76	441.38	496.6	550.99	762.97	496.13	5303
NLD	129.98	410.44	486.41	562.18	794.29	484.78	4765	140.48	452.97	524.34	587.91	792.79	519.23	4765
NOR	153.17	430.32	506.15	575.84	810.56	499.45	5813	163.78	440.56	503.79	565.17	789.19	500.96	5813
POL	154.32	445.69	514.54	581.36	837.35	511.86	5625	192.84	454.78	516.78	577.96	810.78	515.65	5625
PRT	166.58	425.11	497.18	561.93	785.53	491.8	5932	158.4	426.04	497.29	561.71	799.26	492.49	5932
SVK	140.24	387.5	457.5	529.38	780.24	457.98	5965	119.08	419.55	491.72	556.45	801.07	486.16	5965
SWE	128	434.17	511.52	583.49	815.49	505.79	5504	193.5	440.51	504.89	566.84	788.26	502.39	5504

Note. The table presents the descriptive statistics on the reading and math test scores in 2018.

A.5 Trends in intergenerational transmission of learning by country

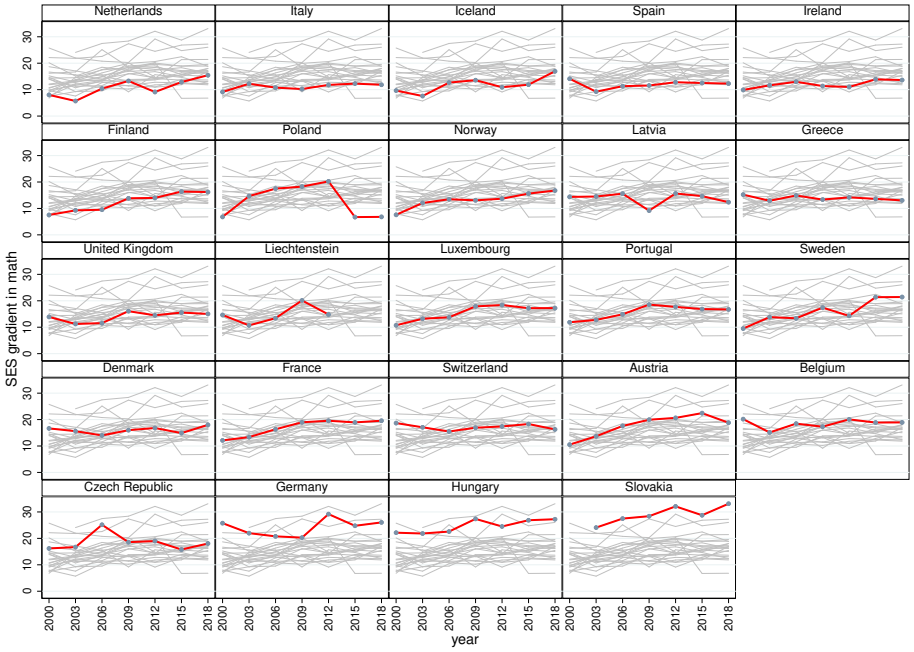
Figure A2: Correlation between SES gradients in math and its lags



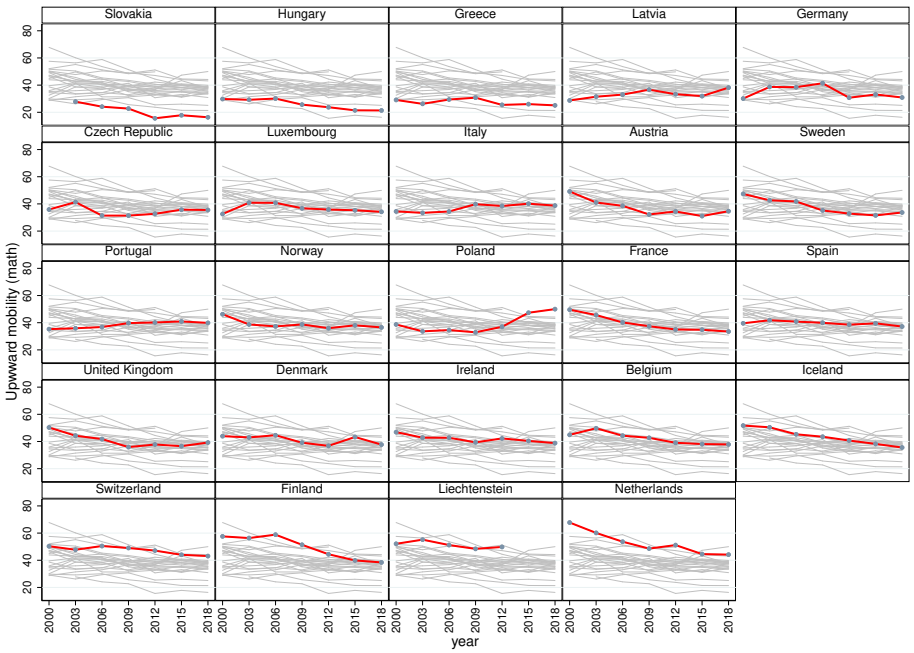
Note. The figures present the correlation between SES gradients in learning (math) in 2018 and its lags. The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of SES gradients in learning correspond to lower mobility. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure A3: Trends in the intergenerational transmission of learning (math) by country.

SES gradient in learning

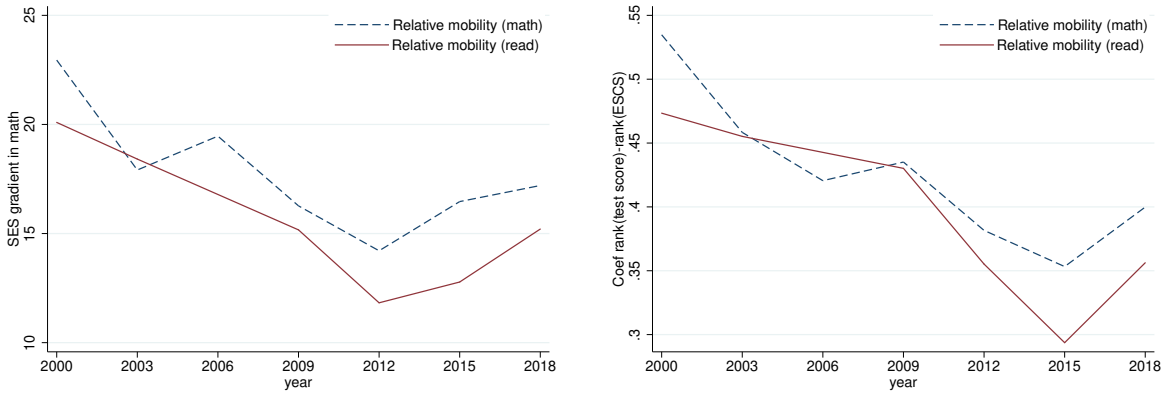


Upward Mobility



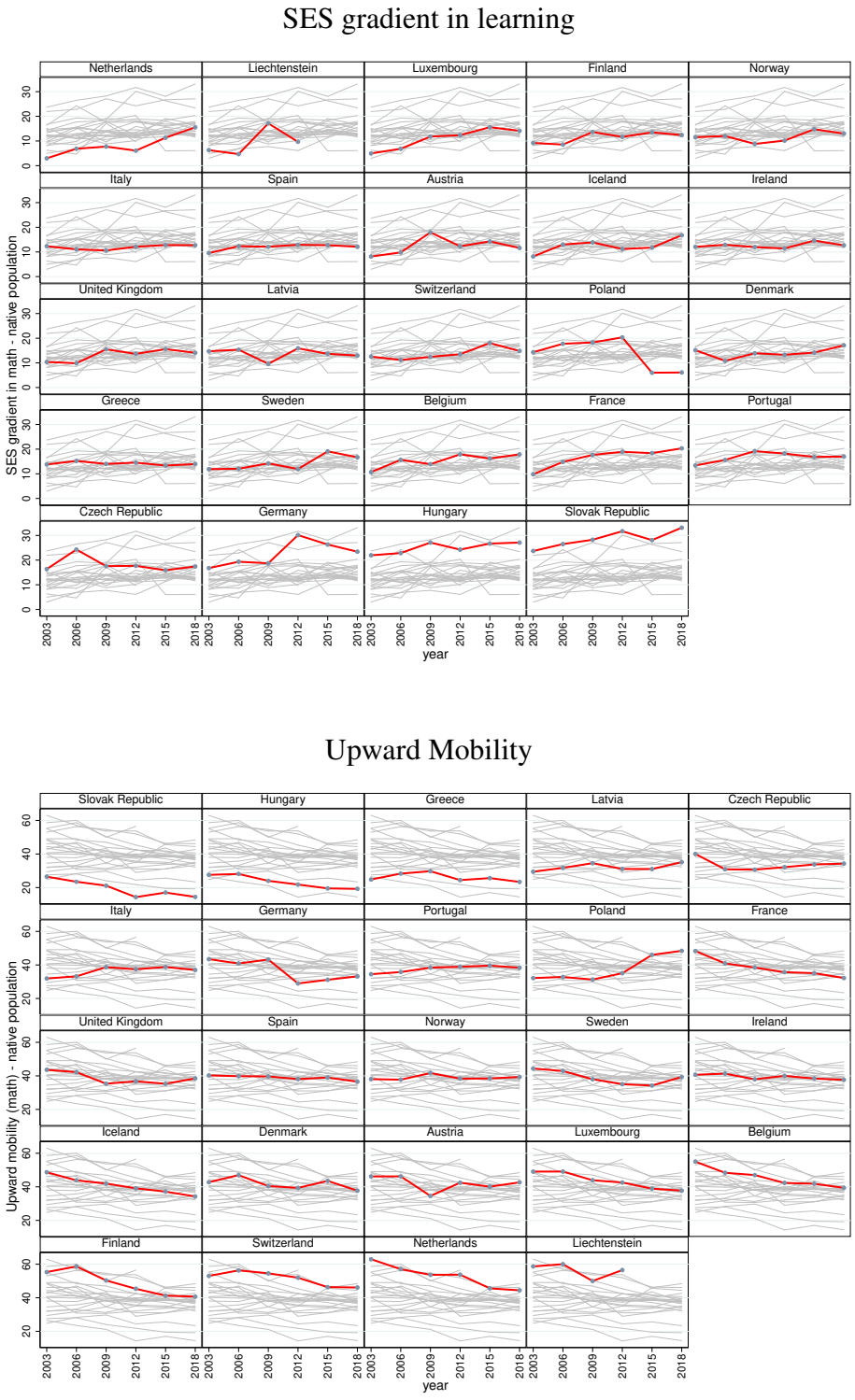
Note. The figures present the trends in the SES gradient and upward mobility for each country (red line) against other countries (gray lines). The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of the SES gradient in learning correspond to lower mobility. Countries are ordered from the most to least mobile, based on the country-average of SES gradients in learning over the PISA waves.

Figure A4: Intergenerational transmission of learning in the United States.



Note. The figures present the measures of intergenerational transmission of learning in the USA over time. The left panel presents the mobility measure computed by regressing the rank of the test score on a dummy equal to 1 if the mother has at least upper secondary (equation (1)). The right panel presents the mobility measure computed by regressing the rank of the test score on the rank of the ESCS index (equation (4)).

Figure A5: Trends in the intergenerational transmission of learning (math) by country (restricting sample to native population).



Note. The figures present the trends in the SES gradient and upward mobility for each country (red line) against other countries (gray lines) restricting the sample to the native population. The estimates are based on equation (1) for the native population, regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level for the native population (i.e., excluding the first- and second-generation immigrants). Higher values of the SES gradient in learning correspond to lower mobility. Countries are ordered from the most to least mobile, based on the country-average of SES gradients in learning over the PISA waves. Immigrant status was not collected in the 2000 PISA wave.

A.6 Do changes in composition drive changes in the intergenerational transmission of learning?

Table A7: intergenerational transmission of learning and migrant students

	SES gradient in learning		**Upward mobility**	
% migrant students	0.014	0.091	0.148	-0.126
	(0.074)	(0.110)	(0.144)	(0.193)
Observations	142	142	142	142
R^2	0.001	0.819	0.036	0.829
Country FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Note. The table presents the regression of the SES gradient and upward mobility (math) on the proportion of first- and second-generation migrant students from the PISA database (2003-2018). The estimates of upward and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The estimates are presented with and without country and year fixed effects. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Table A8: intergenerational transmission of learning and mothers' education

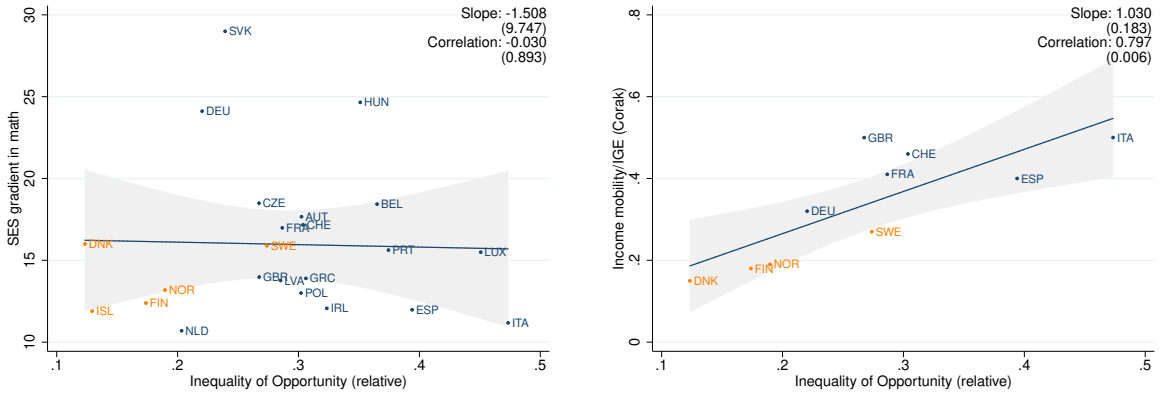
	SES gradient in learning		**Upward mobility**	
% mothers with less than upper secondary education	-0.107	-0.027	0.127	0.119
	(0.070)	(0.105)	(0.084)	(0.172)
Observations	142	142	142	142
R^2	0.076	0.817	0.044	0.830
Country FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Note. The table presents the regression of the SES gradient and upward mobility (math) on the proportion of mothers with less than upper secondary education from the PISA database (2003-2018). The estimates of upward mobility and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The estimates are presented with and without country and year fixed effects. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

B Correlates: intergenerational transmission of learning

B.1 Intergenerational transmission of learning and inequality of opportunity (relative)

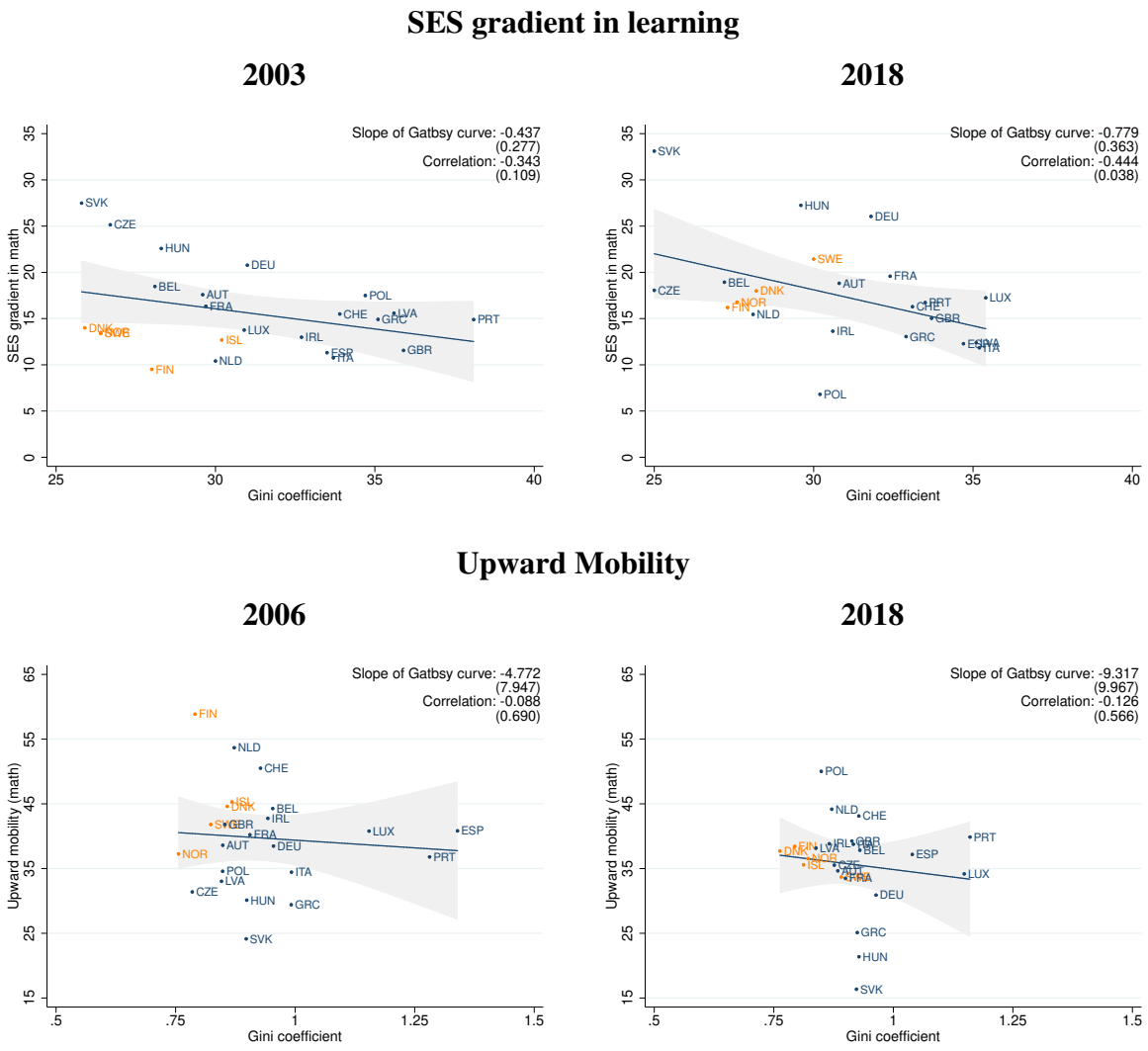
Figure B1: Correlation between SES gradients in learning, inequality of opportunity, IGE (Corak, 2013)



Note. The left figure presents the correlation between SES gradients in learning (math - averaged over PISA years) and inequality of opportunity (relative) in 2010 from https://www.equalchances.org/. The right figure present the correlation between income mobility measure from Corak (2013) and inequality of opportunity (relative) from https://www.equalchances.org/. Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). Equality of opportunity captures to what extent individuals - exerting the same degree of effort (or responsibility) - attain the same level of advantage (or well-being), regardless of any predetermined circumstances beyond their control (Roemer, 1998). The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

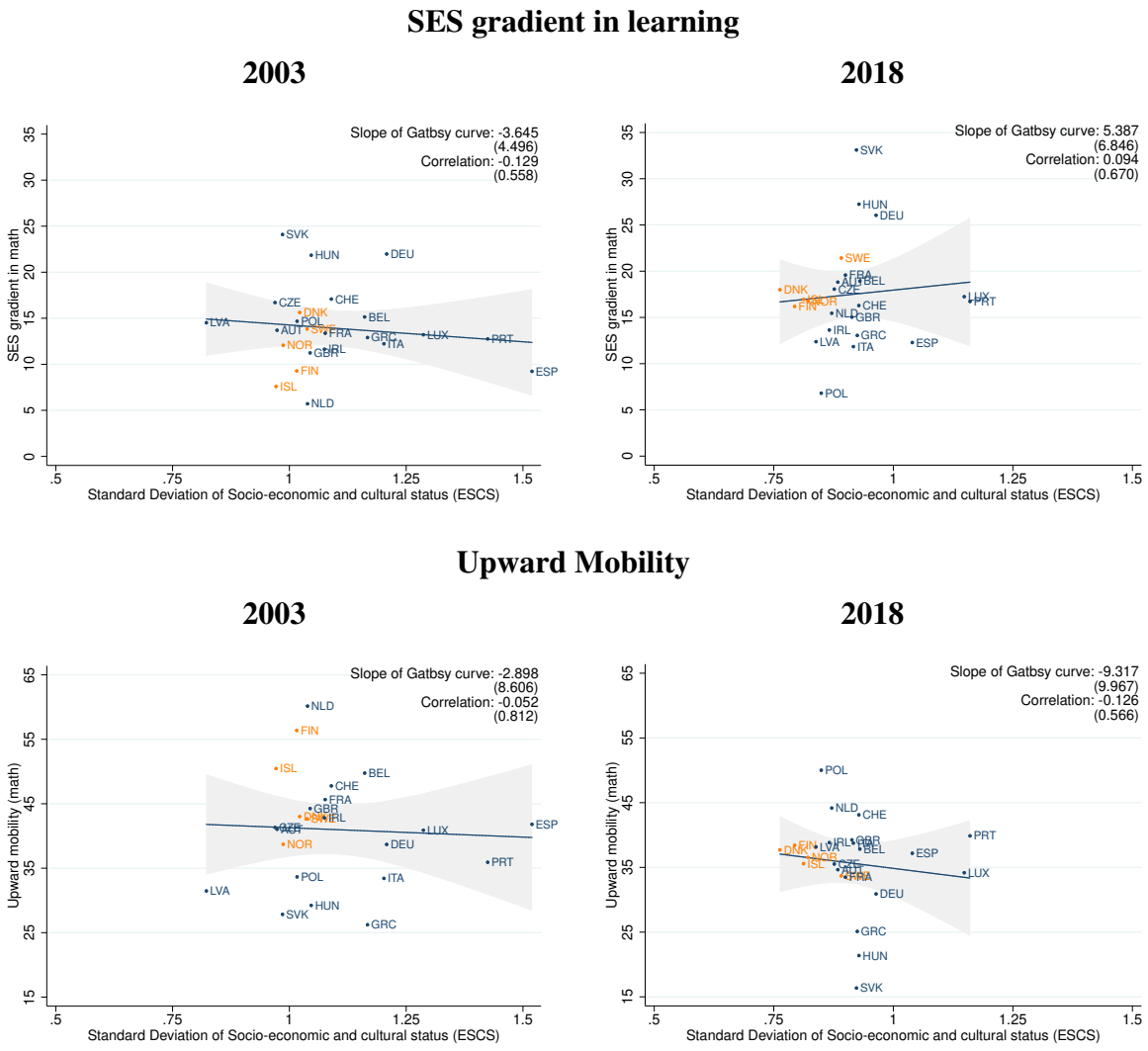
B.2 The Great Gatsby curve

Figure B2: The Great Gatsby curves: intergenerational transmission of learning and Gini coefficient (World Bank).



Note. The figures present the Gatsby curves by year. The estimates of SES gradients in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the Gini Coefficient from the World Bank database in the year of the PISA test. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure B3: The Great Gatsby curves: intergenerational transmission of learning and standard deviation of ESCS index.



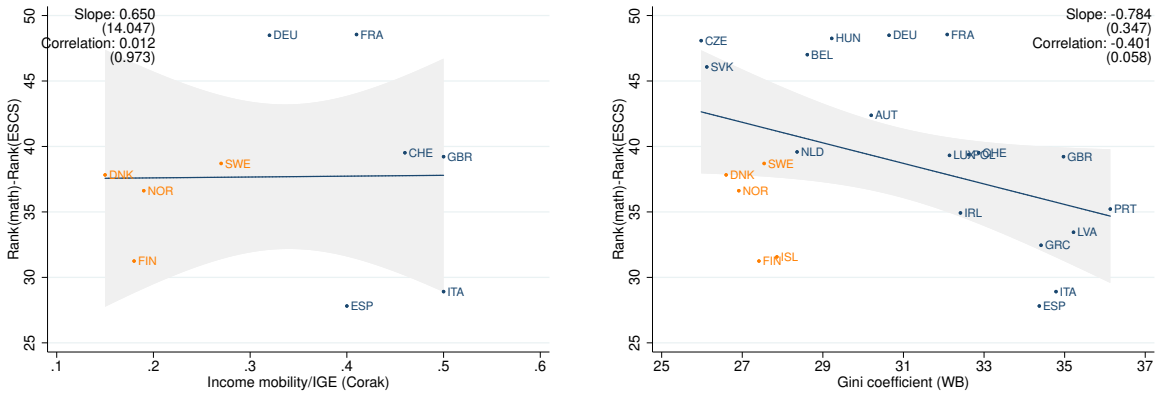
Note. The figures present the Gatsby curves by year. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the standard deviation of ESCS index. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Table B1: Robustness to other definitions: intergenerational transmission of learning and intra/intergenerational inequality

	SES gradient in learning					
Definition	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
Gini coefficient (WB)	-0.502	-0.367	-0.458	-0.032	-0.102	-0.784**
	(0.316)	(0.242)	(0.280)	(0.201)	(0.207)	(0.347)
Observations	23	23	23	23	23	23
R^2	0.105	0.083	0.115	0.001	0.010	0.161
	SES gradient in learning					
Definition	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
Income mobility/IGE (Corak)	2.609	-0.975	-3.730	-6.560	2.577	0.650
	(7.610)	(6.550)	(6.063)	(4.542)	(6.121)	(14.047)
Observations	10	10	10	10	10	10
R^2	0.007	0.001	0.022	0.147	0.015	0.000

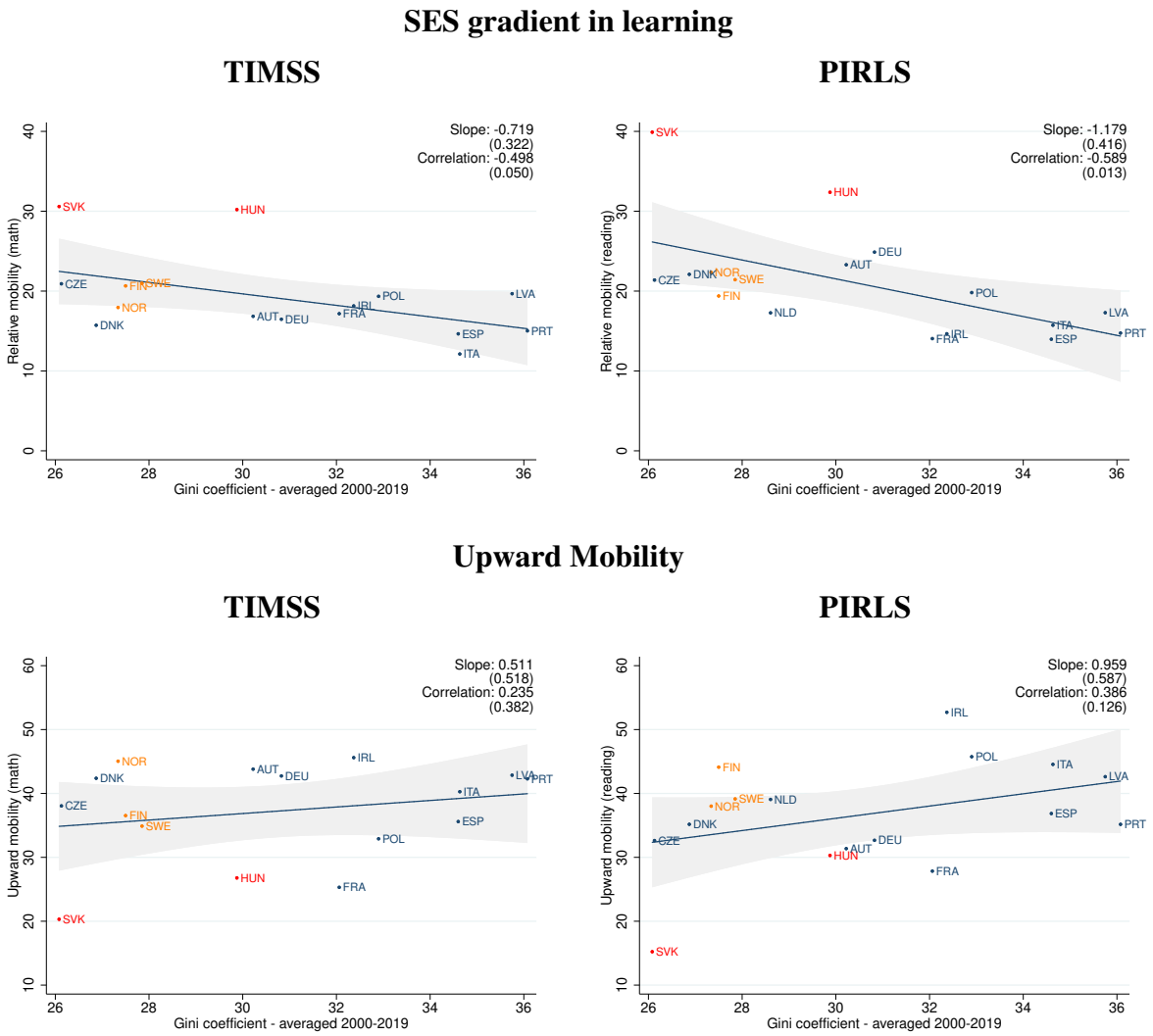
Note. The table presents the robustness to other definitions of learning mobility for the relationship between learning mobility and learning mobility and intra/intergenerational inequality. The other measures are defined in Appendix A.3 and reported in the note of the Table. $\beta_{tc}^{math-father}$ is the measure of the SES gradient in learning in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of the SES gradient in reading from equation (1), β_{tc}^{math-c} is the SES gradient in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is the SES gradient in math from equation (3), $\beta_{tc}^{math-med}$ is the SES gradient in math from equation (5), ρ_{tc}^{math} is the SES gradient from equation (4) using the rank of the parents' ESCS. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Figure B4: Correlation between rank(math)-rank(ESCS), IGE (Corak, 2013), and Gini coefficient



Note. The Left Figure presents the correlation between the coefficient from the rank(math)-rank(ESCS) regression (averaged over PISA years) and income mobility measure from Corak (2013). Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). The Right Figure present the correlation between the coefficient from the rank(math)-rank(ESCS) regression and Gini coefficient from the World Bank (averaged over all PISA years). The estimates of the coefficient from the rank(math)-rank(ESCS) regression are based on a regression of the rank of the math score on the rank of ESCS. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

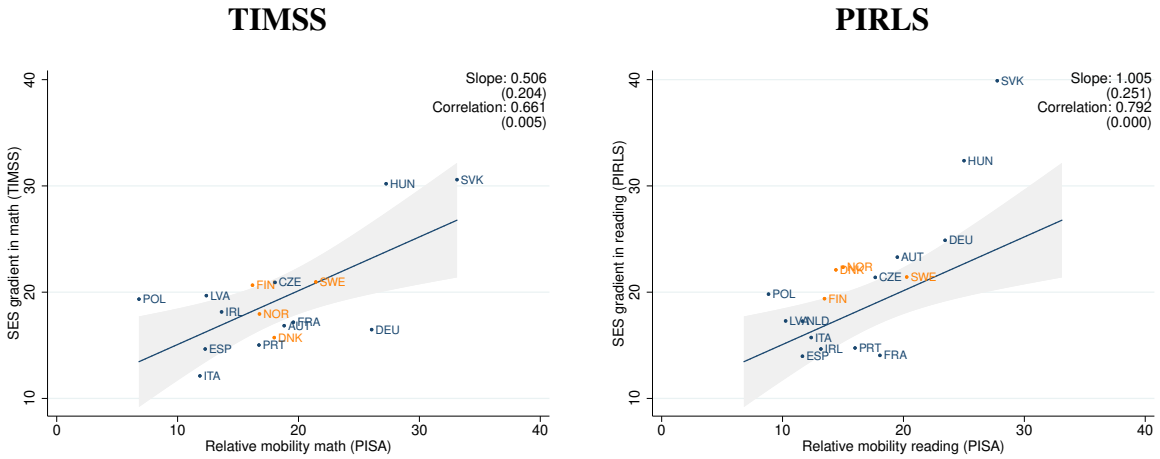
Figure B5: The Great Gatsby curves: intergenerational transmission of learning from TIMSS & PIRLS and Gini coefficient (World Bank).



Note. The figures present the Gatsby curves using the TIMSS and PIRLS data. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score (4-grade 2019 TIMSS)/ reading score (4-grade 2016 PIRLS) on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the Gini Coefficient from the World Bank database in the year of the PISA test. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

B.3 Correlation between intergenerational transmission of learning in PISA and TIMSS/PIRLS

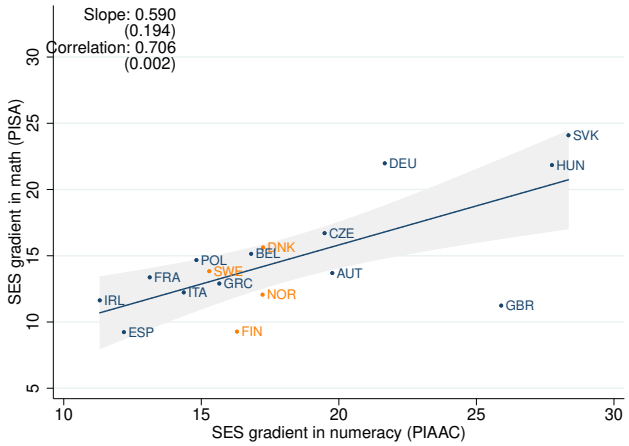
Figure B6: Correlation between intergenerational transmission of learning in PISA and TIMSS/PIRLS



Note. The figure presents the correlation between intergenerational transmission of learning in PISA and TIMSS. The mobility measure is the β_{tc}^{k} of regressing the rank of math skill on a dummy equal to 1 if the mother has at least upper secondary ((1)). The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score (4-grade 2019 TIMSS)/ reading score (4-grade 2016 PIRLS) on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

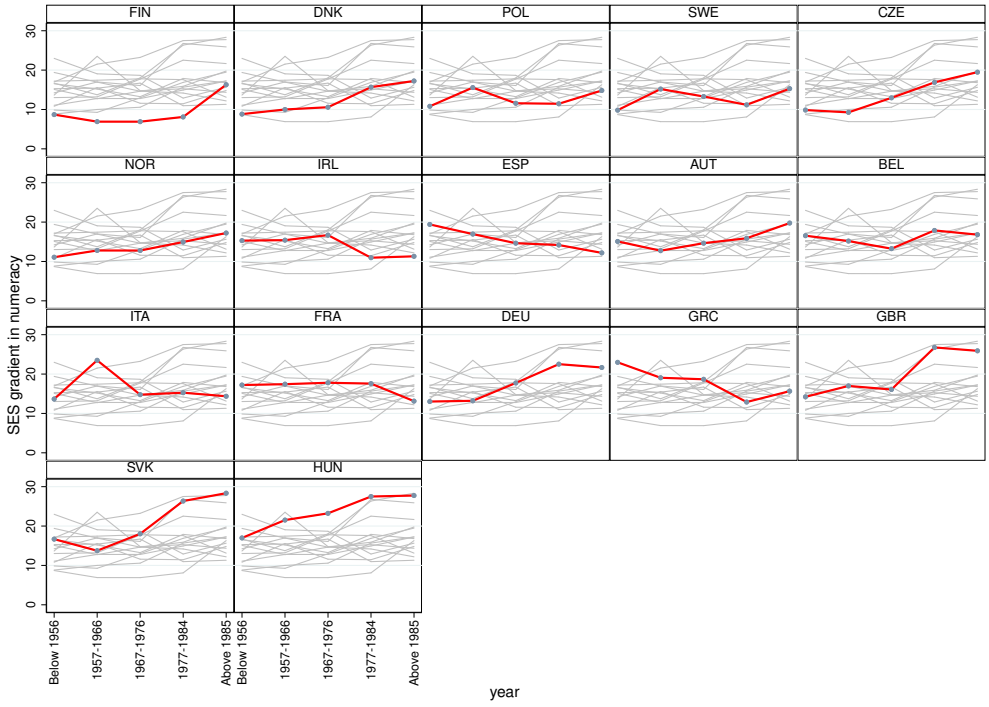
B.4 Evidence from PIAAC data

Figure B7: Correlation between intergenerational transmission of learning in PISA and PIAAC



Note. The figure presents the scatter plots between SES gradients in math (PISA) and SES gradients in numeracy (PIAAC) for the 2003 PISA cohort (i.e., the cohort overlapping with PIAAC one - born 1987 or later). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure B8: Trends in SES gradients in numeracy skill by cohort (PIAAC data).



Note. The figure presents the trends in SES gradients in numeracy skill by cohort. The mobility measure is the β^k_{tc} of regressing the rank of numeracy skill on a dummy equal to 1 if the mother has at least upper secondary. The rank is at European and cohort level.

B.5 SES gradients in parental investment

B.5.1 Measuring parental investment

To construct a measure of parental investment in home educational resources that is comparable across countries and over time, we use a factor model specified in equation (6).

Assuming each latent item, $m^{*,j}_{ict}$ for question j, is additively separable in the logarithm of the latent factor, we have:

$$m^{*,j}_{ict} = \alpha^j_{ct} + \lambda^{j\top}_t lnI_{ict} + \varepsilon^j_{ict} \tag{6}$$

Depending on the nature of $m^{*,j}_{ict}$, we need to specify different models:

(i) Continuous variables: $m_{ict-1} = m^*_{ict-1}$;

(ii) Binary variables $m_{ict-1} \in \{0,1\}$: $Prob\{m_{ict-1} = 1\} = Pr\{m^*_{ict-1} \geq 0\}$;

(iii) Categorical variables $m_{ict-1} \in \{1,2,...,L\}$: $Prob\{m_{ict-1} = l\} = Pr\{\tau_{l-1} \leq m^*_{ict-1} \leq \tau_l\}$, where $\tau_0 = -\infty$;

We use the threshold model defined in (iii) as items are categorical. Given that factors are unobserved and lack a scale, ensuring comparability requires some identification. To achieve

this, we fix the scale and location based on the same item $j = 1$ across countries and over time. Namely, we set $\lambda^1_{ct} = 1$ and $\tau^1_{c1,t} = 0$ and $\alpha^j_{ct} = 0, \forall j$ respectively. We use the following item "Possessions poetry" which has been asked across all the waves and countries. We use the weights provided by the OECD throughout the analysis to estimate the factor model.

The questions used for the parental investment index have been collected from 2003 and are presented below:[3]

- Possessions desk
- Possessions study place
- Possessions computer
- Possessions software
- Possessions textbooks
- Possessions <technical reference books>
- Possessions dictionary
- Possessions literature
- Possessions poetry
- Possessions art
- How many books at home

For each student i, country c and cohort t, we estimate:

$$R(I_{itc}) = \alpha^I_{tc} + \beta^I_{tc} HS^P_{itc} + e_{itc} \tag{7}$$

where $R(I_{itc})$ is the parental investment percentile rank (rank computed at European level) for student i, at time t, living in country c. HS^p_{itc} is an indicator variable taking value 1 if i's mother has completed at least upper secondary education, and 0 otherwise (Appendix Table A2).

β^I_{tc} measures the SES gradient in parental investment; i.e., the association between mother's education (high school degree) and her child's rank in distribution of parental investment, for cohort t and country c.

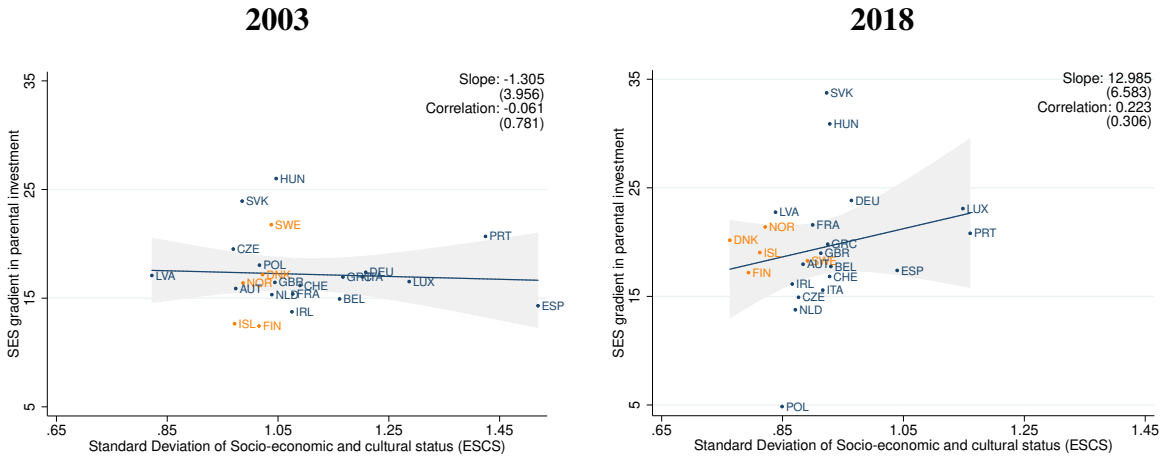
α^I_{tc} measures the average level of investment in children whose mothers do not have upper secondary education.

[3]More details on the questions can be found in the technical reports. Technical report 2003: page 283 https://www.oecd.org/education/school/programmeforinternationalstudentassessmentpisa/35188570.pdf Technical report 2006: Page 316 https://www.oecd.org/pisa/data/42025182.pdf Technical report 2009: page 288 https://www.oecd.org/pisa/pisaproducts/50036771.pdf Technical report 2012: page 316 https://www.oecd.org/pisa/pisaproducts/PISA-2012-technical-report-final.pdf Technical report 2015: page 304 https://www.oecd.org/pisa/data/2015-technical-report/PISA2015_TechRep_Final.pdf

B.5.2 Correlates of the socio-economic gradients in parental investment

Appendix Figure B9 shows a lack of correlation between inequality in ESCS and SES gradients in parental investments, hinting that inequality in the ESCS and SES gradients in parental investment are measuring two different factors.

Figure B9: Correlation between SES gradients in parental investment and inequality in ESCS.

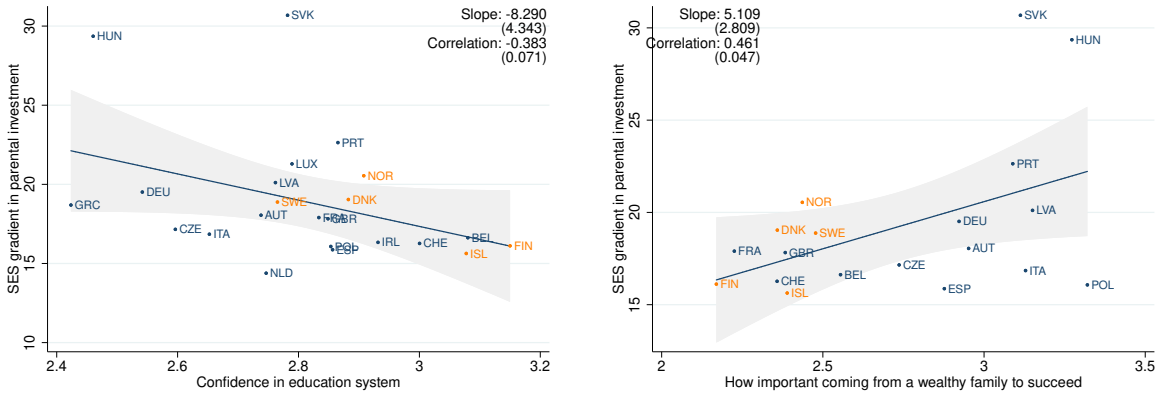


Note. The figures present the correlation between the SES gradients in parental investment and inequality in ESCS. The estimates of the socio-economics gradients in parental investment are based on regression of the rank of the parental investment on a dummy equal to 1 if mother has at least upper secondary (equation (7)). The rank is computed at the European level. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Appendix Figure B10 explores to what extent attitudes towards education correlate with SES gradients in parental investment, aiming to investigate the underlying mechanism. We use the data from the European Value Study (EVS) in 2008 and 2017 and the International Social Survey Programme (ISSP) on social inequality in 2009. For the EVS, the question is "How much confidence you have in the education system, is it a great deal, quite a lot, not very much or none at all? (Answers: 1. a great deal, 2. quite a lot, 3. not very much, 4. none at all). We reverse code the variable and recode "cannot choose" as missing (few people answer cannot choose). We then collapse the data to obtain the mean by country, using the weight provided by EVS.

For the ISSP, the question is "How important you think is coming from a wealthy family for getting ahead in life?" (Answers: 1. Essential, 2. Very Important, 3 Fairly Important, 4. Not very important, 5. Not important at all, 8. cannot choose). We reverse code the variable and recode "cannot choose" as missing (few people answer cannot choose). We then collapse the data to obtain the mean by country, using the weight provided by ISSP.

Figure B10: Correlation between the SES gradients in parental investment and attitudes towards education.



Note. The figures present the correlation between the socio-economics gradients in parental investment (averaged over 2003-2018 PISA waves) and attitudes towards education. The estimates of the socio-economics gradients in parental investment are based on regression of the rank of the parental investment on a dummy equal to 1 if mother has at least upper secondary (equation (7)). The rank is computed at the European level. For the EVS, the question is "How much confidence you have in the education system? (answers: 1. none at all, 2. not very much,, 3. quite a lot, 4. a great deal). For the ISSP, the question is "How important you think is coming from a wealthy family for getting ahead in life?" (answers: 1. Not important at all, 2. Not very important, 3 Fairly Important, 4. Very Important, 5. Essential). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

B.6 Robustness: intergenerational transmission of learning and SES gradients in parental investment

Table B2: Cross-section regressions: SES gradient in test scores - Standardized coefs

	SES gradient in math							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita	-0.199							-0.253
	(0.167)							(0.240)
Returns to secondary school		0.450*						0.007
		(0.217)						(0.154)
Difference between top and lowest tax rates on personal income			-0.187					0.128
			(0.265)					(0.166)
Government expenditure on education (% of GDP)				-0.146				0.262
				(0.167)				(0.172)
School tracking age					-0.490***			-0.525**
					(0.158)			(0.224)
School segregation						0.606***		0.029
						(0.171)		(0.266)
SES gradient in parental investment							0.755***	0.518**
							(0.115)	(0.192)
Observations	24	22	23	23	23	23	24	20
R^2	0.040	0.193	0.034	0.020	0.369	0.352	0.570	0.739

Note. The table presents the cross-sectional estimates of the SES gradient in learning on economic variables with the standardized coefficients. Variables are standardized to have mean 0 and standard deviation 1. The estimates of upward mobility and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B3: Robustness to outliers in the cross section: intergenerational transmission of learning and SES gradients in parental investment

	SES gradient in learning (math)					
Excluding	AUT	BEL	CHE	CZE	DEU	DNK
SES gradient in parental investment	0.845***	0.866***	0.864***	0.858***	0.825***	0.841***
	(0.129)	(0.124)	(0.125)	(0.127)	(0.140)	(0.128)
Observations	23	23	23	23	23	23
R^2	0.579	0.605	0.593	0.598	0.643	0.570
Excluding	ESP	FIN	FRA	GBR	GRC	HUN
SES gradient in parental investment	0.828***	0.831***	0.845***	0.838***	0.840***	0.849***
	(0.132)	(0.132)	(0.129)	(0.128)	(0.127)	(0.187)
Observations	23	23	23	23	23	23
R^2	0.560	0.561	0.576	0.569	0.575	0.483
Excluding	IRL	ISL	ITA	LIE	LUX	LVA
SES gradient in parental investment	0.828***	0.828***	0.824***	0.879***	0.859***	0.853***
	(0.131)	(0.133)	(0.130)	(0.121)	(0.123)	(0.123)
Observations	23	23	23	23	23	23
R^2	0.563	0.558	0.570	0.586	0.584	0.590
Excluding	NLD	NOR	POL	PRT	SVK	SWE
SES gradient in parental investment	0.821***	0.862***	0.836***	0.881***	0.678***	0.841***
	(0.137)	(0.119)	(0.131)	(0.114)	(0.150)	(0.128)
Observations	23	23	23	23	23	23
R^2	0.548	0.604	0.562	0.599	0.362	0.570

Note. The table presents the robustness to outliers for intergenerational transmission of learning and SES gradients in parental investment. The relationship between intergenerational transmission of learning and SES gradients in parental investment is re-estimated by excluding each country one by one. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B4: Robustness to compositional changes: cross section

	SES gradient in learning				
SES gradient in parental investment	0.841***	0.803***	0.870***	0.836***	0.661**
	(0.128)	(0.108)	(0.146)	(0.127)	(0.240)
% migrant students			0.057	0.075	-0.029
			(0.083)	(0.083)	(0.104)
% mothers with less than upper secondary education		-0.070**		-0.079**	-0.129***
		(0.032)		(0.029)	(0.042)
Observations	24	24	24	24	21
R^2	0.570	0.608	0.585	0.633	0.758
Other controls	No	No	No	No	Yes
	Upward mobility				
SES gradient in parental investment	-1.483***	-1.461***	-1.427***	-1.415***	-1.057***
	(0.174)	(0.182)	(0.185)	(0.197)	(0.242)
% migrant students			0.109	0.103	-0.087
			(0.073)	(0.077)	(0.152)
% mothers with less than upper secondary education		0.043		0.029	0.069
		(0.069)		(0.076)	(0.091)
Observations	24	24	24	24	21
R^2	0.646	0.651	0.666	0.668	0.781
Other controls	No	No	No	No	Yes

Note. The table shows that the association in the cross section between the SES gradient in learning outcomes and the SES gradient in parental investment remains robust, when controlling for compositional factors, such as the percentage of first/second-generation migrant students and the percentage of mothers with less than a high school education. Other controls are: *socio-economic variables* (returns to secondary school from the OECD, and country GDP per capita from the World Bank database); *institutional variables* (the progressivity of the tax system, proxied by the difference between the top and lowest tax rates on personal income, and spending in public education from the World Bank database) and *education system variables* (age at which academic tracking starts from Eurydice and school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects). Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B5: Robustness to other definitions in the cross section: intergenerational transmission of learning and SES gradients in parental investment

			SES gradient in learning			
Panel A **Definition**	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
SES gradient in parental investment	0.935***	0.714***	1.022***	1.132***	0.445***	35.650**
	(0.096)	(0.105)	(0.153)	(0.211)	(0.144)	(15.735)
Observations	24	24	24	24	24	23
R^2	0.687	0.492	0.649	0.631	0.275	0.198
Other controls	No	No	No	No	No	No
Panel B						
SES gradient in parental investment	0.378***	0.457***	0.707***	0.637**	-0.022	11.661
	(0.124)	(0.137)	(0.211)	(0.227)	(0.125)	(9.741)
Observations	74	74	74	74	74	74
R^2	0.925	0.943	0.927	0.925	0.835	0.907
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
			Upward mobility			
Panel C **Definition**	$\alpha_{tc}^{math-father}$	α_{tc}^{read}	α_{tc}^{math-c}	$\alpha_{tc}^{math-uni}$	$\alpha_{tc}^{math-med}$	μ_{tc}^{math}
SES gradient in parental investment	-1.381***	-1.375***	-1.000***	-0.924**	-0.941***	-15.093*
	(0.124)	(0.231)	(0.256)	(0.377)	(0.167)	(8.293)
Observations	24	24	24	24	24	23
R^2	0.662	0.626	0.517	0.164	0.326	0.074
Other controls	No	No	No	No	No	No
Panel D						
SES gradient in parental investment	-1.150***	-0.607*	-0.687*	-0.085	-0.944**	-45.847**
	(0.370)	(0.327)	(0.328)	(0.488)	(0.380)	(15.181)
Observations	20	20	20	20	20	20
R^2	0.717	0.627	0.611	0.573	0.753	0.544
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the robustness in the cross section to other definitions of intergenerational transmission of learning for the relationship between intergenerational transmission of learning and SES gradients in parental investment. The other measures are defined in Appendix A.3 and reported in the note of the table. The socio-economic status variable is defined in the same way for the SES gradient in test scores and SES gradient in parental investment. $\beta_{tc}^{math-father}$ is the measure of the SES gradient in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of the SES gradient in reading from equation (1), β_{tc}^{math-c} is the SES gradient in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is the SES gradient in math from equation (3), $\beta_{tc}^{math-med}$ is the SES gradient in math from equation (5), ρ_{tc}^{math} is the SES gradient from equation (4) using the rank of the parents' ESCS. α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B6: Panel regressions: SES gradient in test scores - Standardized coefs

	SES gradient in math						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	0.705						-0.101
	(0.441)						(0.809)
Returns to secondary school		0.162*					0.059
		(0.081)					(0.125)
Difference between top and lowest tax rates on personal income			0.097				0.297
			(0.223)				(0.382)
Government expenditure on education (% of GDP)				-0.086			-0.054
				(0.143)			(0.145)
School segregation					0.118		0.009
					(0.170)		(0.271)
SES gradient in parental investment						0.513***	0.592***
						(0.117)	(0.195)
Observations	160	118	137	117	159	142	74
R^2	0.805	0.841	0.808	0.819	0.802	0.881	0.914
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the panel estimates of the SES gradient in learning on economic variables with year and country fixed effects with the standardized coefficients. Variables are standardized to have mean 0 and standard deviation 1. The estimates of upward mobility and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Table B7: Robustness to outliers in the panel regression: intergenerational transmission of learning and SES gradients in parental investment

	SES gradient in learning (math)					
Excluding	AUT	BEL	CHE	CZE	DEU	DNK
SES gradient in parental investment	0.557***	0.572***	0.560***	0.552***	0.555***	0.565***
	(0.131)	(0.127)	(0.133)	(0.146)	(0.141)	(0.131)
Observations	136	136	136	136	136	136
R^2	0.882	0.882	0.883	0.892	0.873	0.883
Excluding	ESP	FIN	FRA	GBR	GRC	HUN
SES gradient in parental investment	0.568***	0.554***	0.575***	0.571***	0.570***	0.563***
	(0.129)	(0.132)	(0.127)	(0.129)	(0.129)	(0.131)
Observations	136	136	136	136	136	136
R^2	0.877	0.880	0.883	0.881	0.884	0.863
Excluding	IRL	ISL	ITA	LIE	LUX	LVA
SES gradient in parental investment	0.564***	0.565***	0.560***	0.553***	0.569***	0.573***
	(0.131)	(0.131)	(0.132)	(0.133)	(0.131)	(0.131)
Observations	136	136	136	138	136	136
R^2	0.880	0.882	0.879	0.884	0.882	0.894
Excluding	NLD	NOR	POL	PRT	SVK	SWE
SES gradient in parental investment	0.590***	0.581***	0.392***	0.572***	0.607***	0.593***
	(0.117)	(0.122)	(0.112)	(0.129)	(0.122)	(0.113)
Observations	136	136	136	136	136	136
R^2	0.887	0.885	0.887	0.883	0.841	0.897

Note. The table presents the robustness in the panel to outliers for intergenerational transmission of learning and SES gradients in parental investment. The relationship between intergenerational transmission of learning and SES gradients in parental investment is re-estimated by excluding each country one by one. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Table B8: Robustness to compositional changes: panel regression

			SES gradient in learning		
SES gradient in parental investment	0.564***	0.579***	0.561***	0.575***	0.682***
	(0.129)	(0.120)	(0.127)	(0.120)	(0.189)
% migrant students			0.034	0.025	-0.168
			(0.090)	(0.083)	(0.171)
% mothers with less than upper secondary education		-0.079		-0.078	-0.136
		(0.067)		(0.065)	(0.153)
Observations	142	142	142	142	74
R^2	0.881	0.884	0.882	0.884	0.919
Other controls	No	No	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
			Upward mobility		
SES gradient in parental investment	-0.750***	-0.783***	-0.744***	-0.780***	-0.954***
	(0.229)	(0.212)	(0.227)	(0.212)	(0.230)
% migrant students			-0.050	-0.026	0.464*
			(0.161)	(0.149)	(0.256)
% mothers with less than upper secondary education		0.189		0.188	0.432*
		(0.131)		(0.130)	(0.209)
Observations	142	142	142	142	74
R^2	0.874	0.880	0.874	0.880	0.935
Other controls	No	No	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note. The table shows that the association in the panel between the SES gradient in learning outcomes and the SES gradient in parental investment remains robust, when controlling for compositional factors, such as the percentage of first/second-generation migrant students and the percentage of mothers with less than a high school education. Other controls are: *socio-economic variables* (returns to secondary school from the OECD, and country GDP per capita from the World Bank database); *institutional variables* (the progressivity of the tax system, proxied by the difference between the top and lowest tax rates on personal income, and spending in public education from the World Bank database) and *education system variables* (school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects). Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Table B9: Robustness to other definitions in the panel regression: intergenerational transmission of learning and SES gradients in parental investment

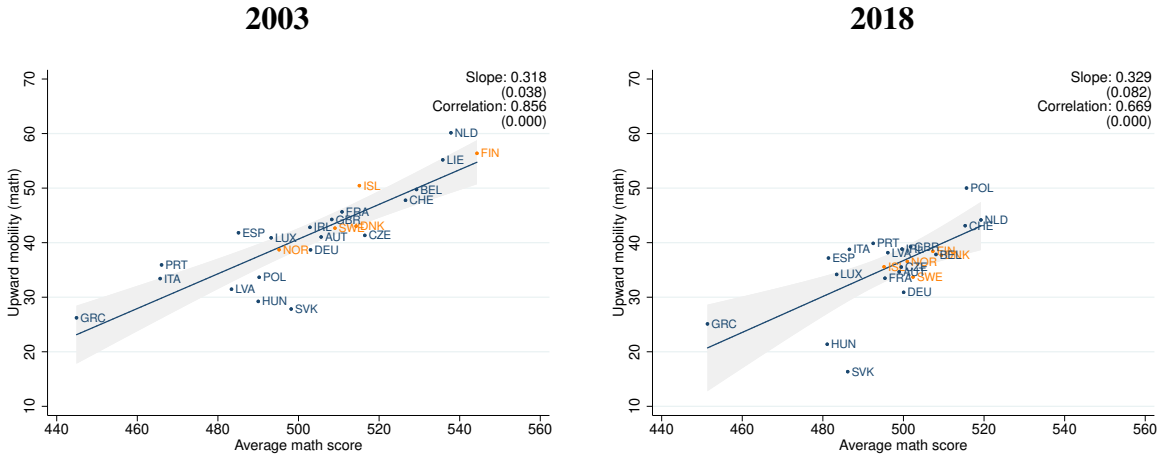
			SES gradient in learning			
Panel A **Definition**	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
SES gradient in parental investment	0.438***	0.502***	0.634***	0.687***	0.138**	18.020
	(0.087)	(0.118)	(0.124)	(0.111)	(0.065)	(11.711)
Observations	142	142	142	142	142	137
R^2	0.889	0.880	0.889	0.857	0.681	0.885
Other controls	No	No	No	No	No	No
Panel B						
SES gradient in parental investment	0.378***	0.457***	0.707***	0.637**	-0.022	11.661
	(0.124)	(0.137)	(0.211)	(0.227)	(0.125)	(9.741)
Observations	74	74	74	74	74	74
R^2	0.925	0.943	0.927	0.925	0.835	0.907
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
			Upward mobility			
Panel C **Definition**	$\alpha_{tc}^{math-father}$	α_{tc}^{read}	α_{tc}^{math-c}	$\alpha_{tc}^{math-uni}$	$\alpha_{tc}^{math-med}$	μ_{tc}^{math}
SES gradient in parental investment	-0.522***	-0.596***	-0.612***	-0.276	-0.285*	-10.382
	(0.160)	(0.167)	(0.149)	(0.190)	(0.139)	(10.635)
Observations	142	142	142	142	142	137
R^2	0.883	0.878	0.903	0.854	0.811	0.749
Other controls	No	No	No	No	No	No
Panel D						
SES gradient in parental investment	-0.549**	-0.416*	-0.709***	-0.126	-0.094	-6.114
	(0.220)	(0.236)	(0.229)	(0.293)	(0.217)	(15.225)
Observations	74	74	74	74	74	74
R^2	0.932	0.931	0.935	0.881	0.892	0.859
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the robustness in the panel to other definitions of intergenerational transmission of learning for the relationship between intergenerational transmission of learning and SES gradients in parental investment. The other measures are defined in Appendix A.3 and reported in the note of the table. The socio-economic status variable is defined in the same way for the SES gradient in test scores and SES gradient in parental investment. $\beta_{tc}^{math-father}$ is the measure of the SES gradient in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of the SES gradient in reading from equation (1), β_{tc}^{math-c} is the SES gradient in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is the SES gradient in math from equation (3), $\beta_{tc}^{math-med}$ is SES gradient in math from equation (5), ρ_{tc}^{math} is the SES gradient from equation (4) using the rank of the parents' ESCS. α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

C Other measures of SES gradients in child outcomes

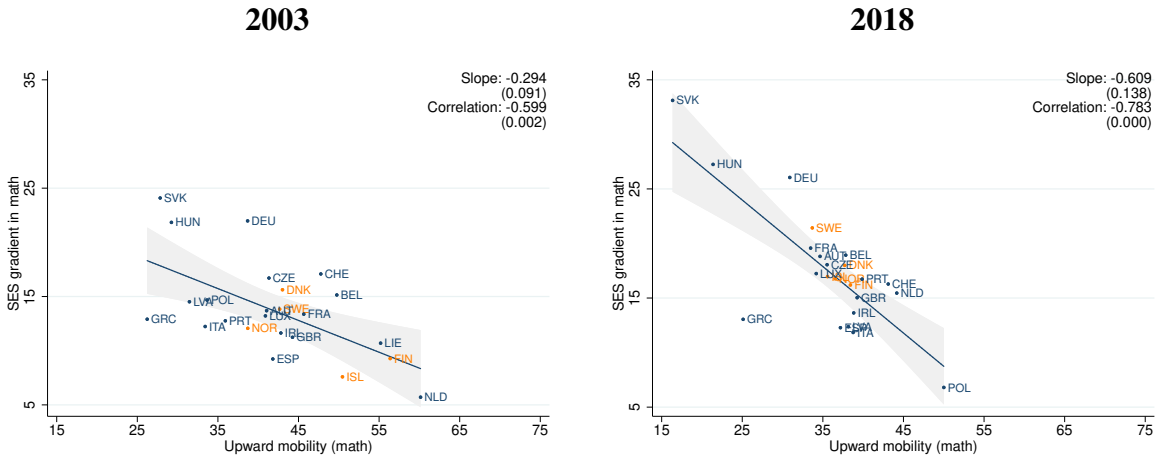
C.1 Upward mobility

Figure C1: Correlation between upward mobility and average math score



Note. The figures present the correlation between upward mobility and average math score. The estimates of upward mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure C2: Correlation between SES gradients in learning and upward mobility (math)



Note. The figures present the correlation between SES gradients in learning and upward mobility (math). The estimates of upward and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

C.2 Panel estimates: upward mobility in test scores

Table C1: Panel regressions: upward mobility in learning

	Upward mobility (math)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	8.172						3.302
	(10.032)						(9.299)
Returns to secondary school		-0.170*					-0.114
		(0.092)					(0.211)
Difference between top and lowest tax rates on personal income			0.107				0.114
			(0.097)				(0.138)
Government expenditure on education (% of GDP)				-1.898			-1.736
				(1.500)			(1.308)
School segregation					-6.633		5.317
					(21.710)		(29.794)
SES gradient in parental investment						-0.750***	-0.801**
						(0.229)	(0.287)
Observations	160	118	137	117	159	142	74
R^2	0.792	0.845	0.815	0.841	0.786	0.874	0.921
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the panel estimates of upward mobility in math scores on economic variables with year and country fixed effects (equation (2)). The estimates of upward mobility and SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

C.3 SES gradients in other traits

To measure students' educational and occupational aspirations, we follow La Ferrara (2019). Occupational aspiration is defined as a dummy equal to 1 for students who expect to have a job with an International Socio-Economic Index of Occupational Status (ISEI)$\geq$65 at the age of 30 - i.e. a white collar job. Educational aspiration is defined as a dummy equal to 1 for students who expect to study at university. Information on educational aspiration is available from the 2003, 2009, 2015 and 2018 waves, while information on occupational aspiration is available in the 2000, 2003, 2006, 2015 and 2018 waves.

Self-efficacy measures the extent to which individuals believe in their own ability to engage in certain activities and perform specific tasks, especially when facing adverse circumstances (Bandura, 1977, 1991). PISA measures self-efficacy in math abilities in 2003 and 2012 by combining students' responses to questions on how confident they feel about having to solve certain calculations.

To measure non-cognitive skills, we look at the probability of being on time to school in 2000, 2003, 2012, 2015, and 2018 (Cunha and Heckman, 2007; Borghans et al., 2008).

It is possible to measure the SES gradient and upward mobility in these traits by estimating equation (1) where the outcome is one of the traits we describe above. Then the SES gradient is the difference in a certain trait between high and low SES and upward mobility is the average outcome of low SES.

Table C2: Correlation among the estimates of SES gradients in other traits in 2003 and 2015

	SES gradient in (2003)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.845***	1				
Science	0.859***	0.965***	1			
Educational aspiration	0.458*	0.298	0.314	1		
Occupational aspiration	0.615**	0.461*	0.493*	0.760***	1	
Being on time to school	0.694***	0.692***	0.782***	0.343	0.528**	1

	SES gradient in (2015)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.936***	1				
Science	0.973***	0.966***	1			
Educational aspiration	0.125	0.220	0.0938	1		
Occupational aspiration	0.236	0.290	0.192	0.810***	1	
Being on time to school	0.597***	0.640***	0.632***	-0.114	-0.0717	1

Note. The table presents the correlation among different SES gradients in other traits in 2003 and 2015. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Table C3: Correlation among the estimates of upward mobility in other traits in 2003, 2015, 2018

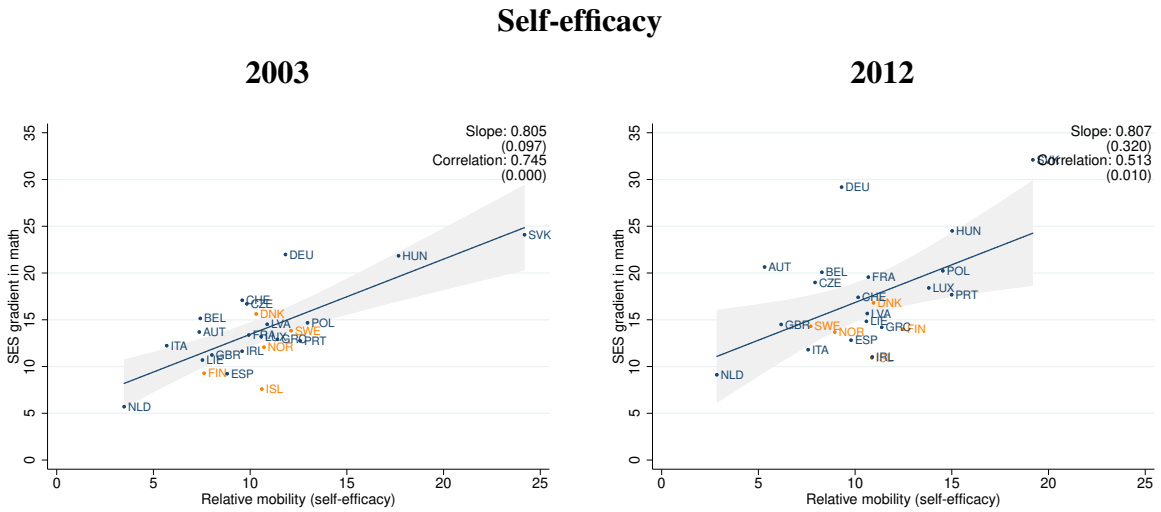
	Upward mobility in (2003)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.726***	1				
Science	0.730***	0.832***	1			
Educational aspiration	-0.151	0.370	0.197	1		
Occupational aspiration	0.244	0.732***	0.437	0.720***	1	
Being on time to school	0.262	-0.213	-0.0826	-0.637**	-0.756***	1

	Upward mobility in (2015)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.826***	1				
Science	0.887***	0.927***	1			
Educational aspiration	0.131	0.158	0.179	1		
Occupational aspiration	0.239	0.342	0.312	0.316	1	
Being on time to school	0.109	0.288	0.285	-0.0259	0.290	1

	Upward mobility in (2018)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.889***	1				
Science	0.934***	0.949***	1			
Educational aspiration	0.416**	0.482**	0.460**	1		
Occupational aspiration	0.610***	0.679***	0.568***	0.570***	1	
Being on time to school	0.196	0.369*	0.253	0.203	0.445**	1

Note. The table presents the correlation among different measures of upward mobility in 2003, 2015 and 2018. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Figure C3: Correlation between SES gradients in learning (math) and SES gradients in self-efficacy.



Note. The figures present the correlation between SES gradients in learning (math) and SES gradients in self-efficacy. The estimates of the SES gradient in learning are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

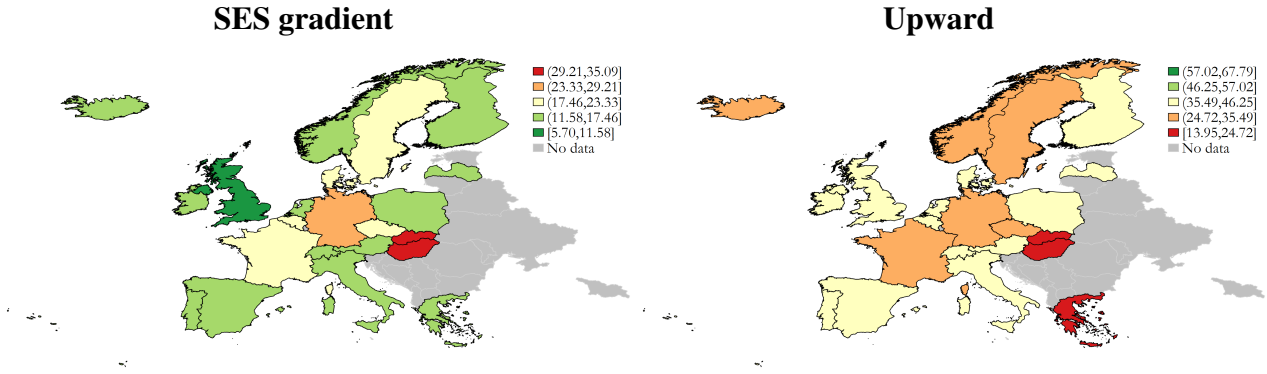
Table C4: SES gradients in other traits and SES gradients in parental investment

	SES gradient in					
	Read	Science	Occupational aspiration	Educational aspiration	Being on time	Self-efficacy
SES gradient in parental investment	0.714***	0.708***	0.009***	0.012***	0.005*	0.709***
	(0.105)	(0.129)	(0.001)	(0.002)	(0.002)	(0.128)
Observations	24	24	24	24	24	24
R^2	0.492	0.435	0.545	0.486	0.152	0.644

Note. The table presents the correlation between SES gradients in other traits and the socio-economic gradient in parental investment (averaged over the PISA years). The estimates of the SES gradient are based on equation (1), regression of trait on a dummy equal to 1 if mother has at least upper secondary. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

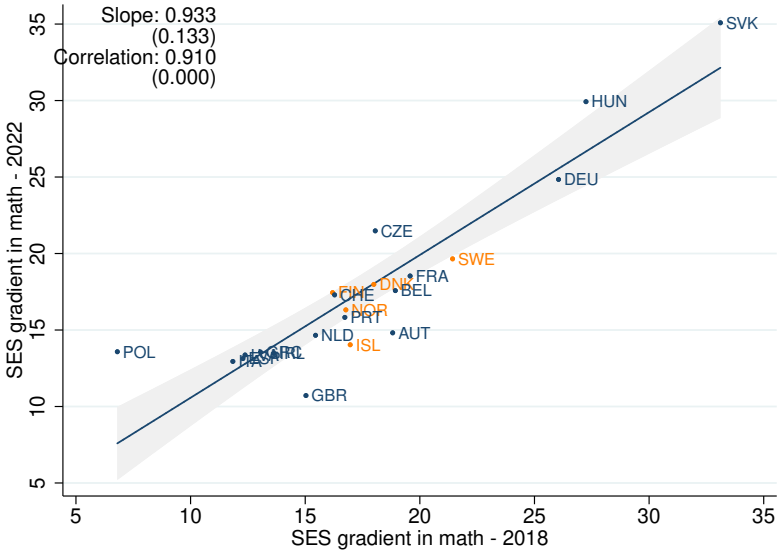
D 2022-PISA wave

Figure D1: Heat map of intergenerational transmission of learning (math score) in 2022



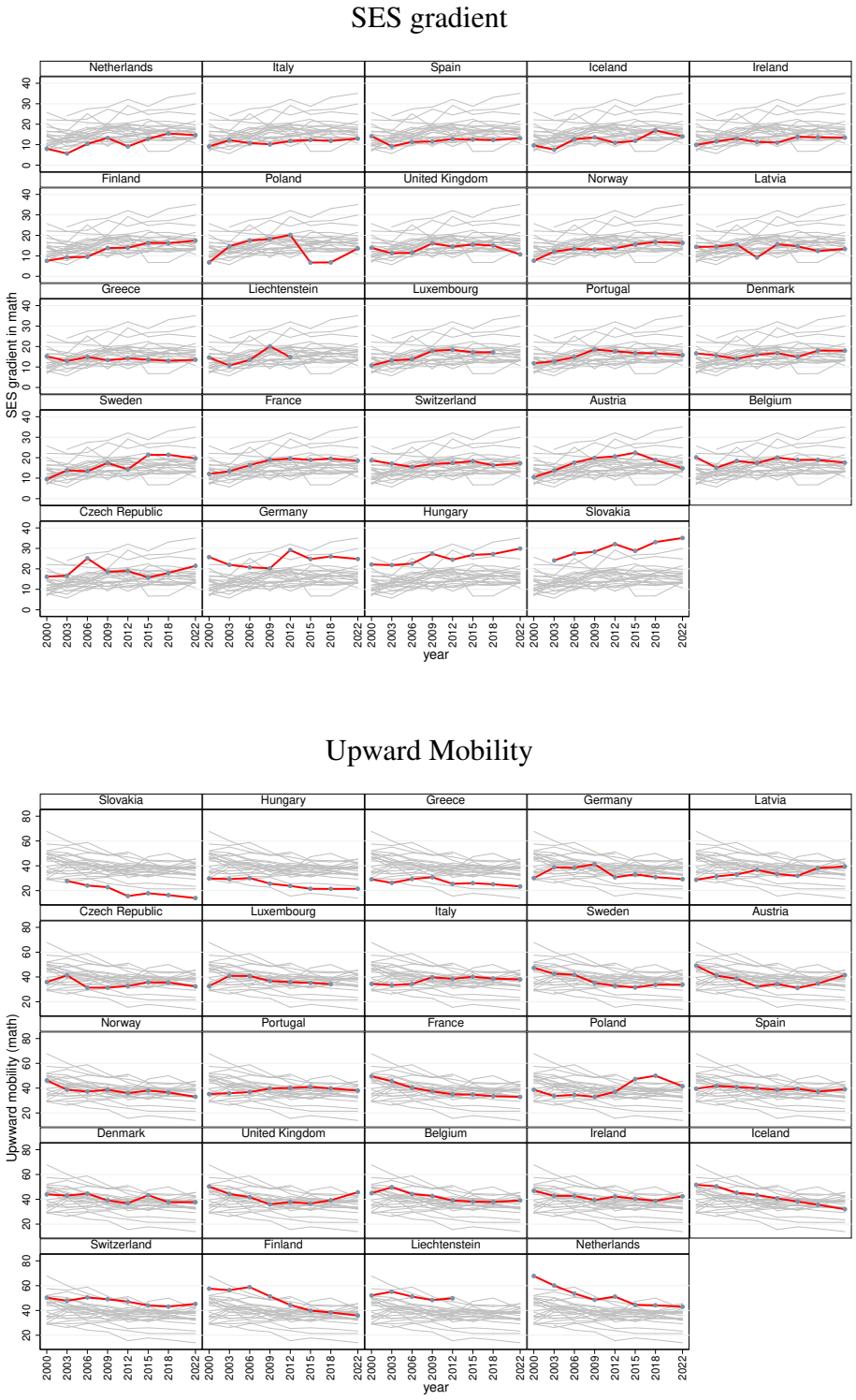
Note. The heat maps present the estimates of intergenerational transmission of learning for each country in 2022 (the estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least upper secondary). The SES gradient in learning measure is β_{tc}^{math} from equation (1). The upward mobility (α_{tc}^{math}) is the average rank of test score of children whose mothers do not have upper secondary. The rank is computed at the European level. Green areas are the most mobile and red areas are the least mobile. The intervals are the same for each year.

Figure D2: Correlation between SES gradient in learning (math) before and after COVID-19 (2018 vs. 2022-PISA wave)



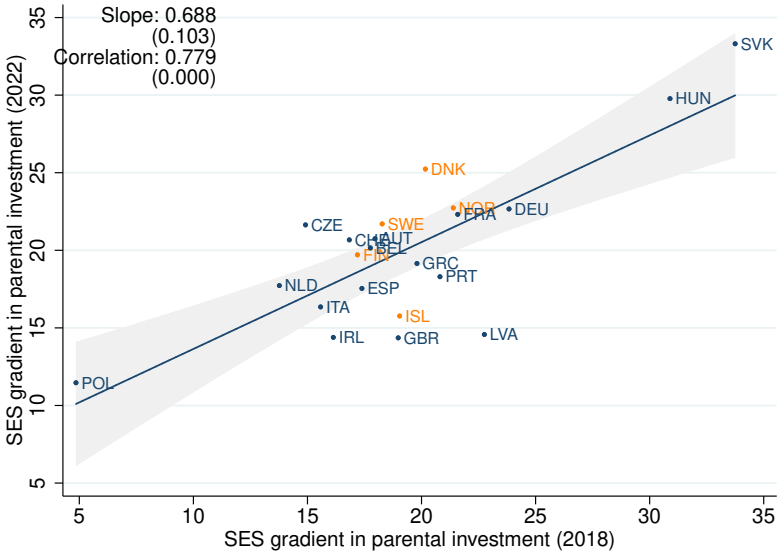
Note. The figure presents the scatter plots between SES gradients in learning (math) before and after COVID-19 (2018 vs. 2022-PISA wave). The estimates of the SES gradient in learning are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D3: Trends in intergenerational transmission of learning (math) by country with 2022-PISA wave.



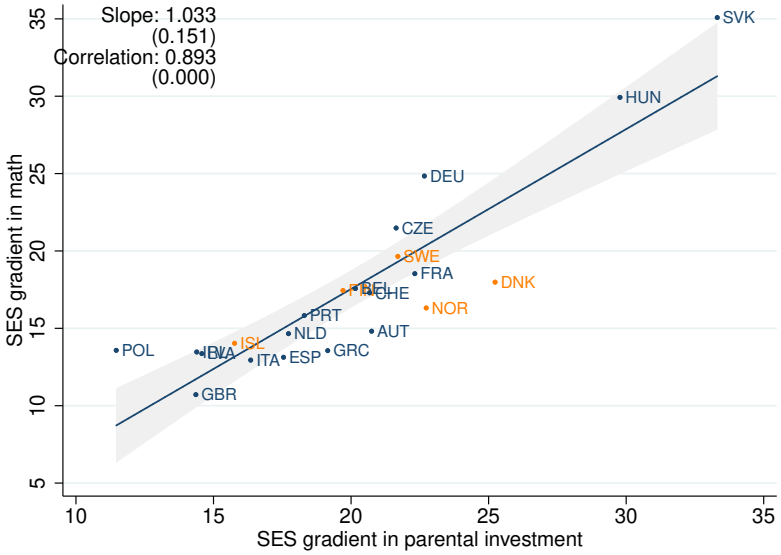
Note. The figures present the trends in the SES gradient and upward mobility for each country with 2022-PISA wave (red line) against other countries (gray lines). The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of the SES gradient in learning correspond to lower mobility. Countries are ordered from the most to least mobile, based on average mobility over the PISA waves.

Figure D4: Correlation between SES gradients in parental investment before and after COVID-19 (2018 vs. 2022-PISA wave)



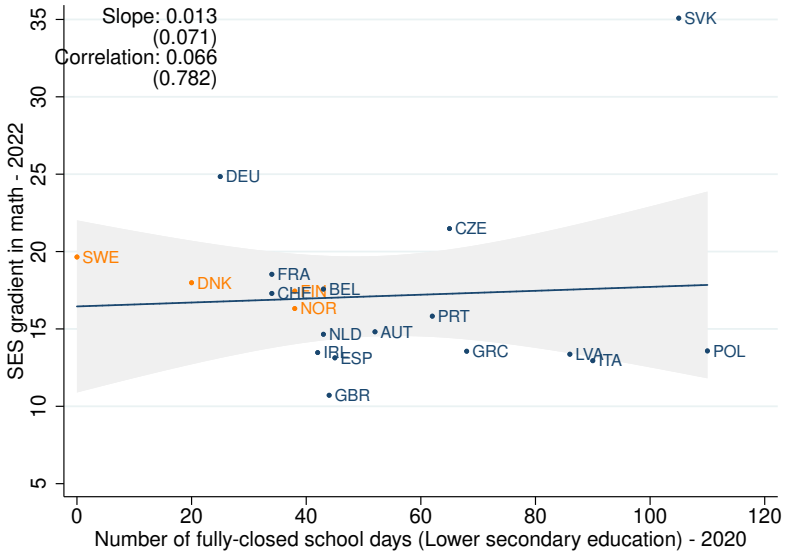
Note. The figure presents the scatter plots between SES gradients in parental investment before and after COVID-19 (2018 vs. 2022-PISA wave). Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The estimates of the SES gradient in parental investment are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D5: Correlation between SES gradients in learning (math) and SES gradients in parental investment after COVID-19 (2022-PISA wave)



Note. The figure presents the scatter plots between SES gradients in learning (math) and SES gradients in parental investment after COVID-19 (2022 PISA wave). The estimates of the SES gradient in learning are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D6: Correlation between SES gradients in learning (math) after COVID-19 (2022-PISA wave) and the number of fully-closed school days (Lower secondary education) in 2020



Note. The figure presents the scatter plots between SES gradients in learning (math) after COVID-19 (2022-PISA wave) and the number of fully-closed school days (Lower secondary education) in 2020. The estimates of the SES gradient in learning are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. The number of fully-closed school days (Lower secondary education) in 2020 is from OECD (2021). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.